SCREENING AND SUFFICIENCY IN MULTIOBJECTIVE DECISION PROBLEMS WITH LARGE ALTERNATIVE SETS

THESIS

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Abstract

Portfolio selection problems with combinatorially-large alternative sets can be impossible to evaluate precisely on a reasonable timescale. When portfolios require complex modeling for performance assessment, prohibitive computational processing times can result. Eliminating a small number of alternatives through an intelligent screening process can greatly reduce the number of alternative combinations, thereby decreasing a problem's evaluation time and cost.

A methodology was developed for the class of hierarchical portfolio selection problems in which multiple objectives are all judged on the same sub-objectives. First, a novel capability-based alternative screening process was devised to identify and remove poor alternatives, thereby reducing the number of portfolios. Then, a performance-based portfolio screening process was explored to estimate portfolio sufficiency according to the performance requirements of the decision maker. Following the establishment of a set of sufficient portfolios, the analyst can employ higher resolution post-analysis methods to choose a final solution.

Finally, the methodology was applied to a portfolio selection problem in which the United States Strategic Command attempts to select an ideal mix of intelligence, surveillance, and reconnaissance assets. After deconstructing the actual objective hierarchy, a set of representative alternatives were evaluated and a variety of screening procedures were applied to demonstrate significant reduction in the number of possible portfolios.

To my family

Acknowledgments

I owe significant gratitude to Dr. Jeffery Weir, my faculty advisor and teacher of the field of Decision Analysis. Dr. Weir's flexibility has been invaluable in the process of this research. Without his understanding and guidance, this work would not have been possible. I also owe thanks to committee member Lt Col. Stephen Chambal for his advice on clarifying and better relating theory to the operational environment. Finally, I appreciate the efforts of Dr. James Chrissis to facilitate my enrollment in the Operations Research program, which has broadened my education and allowed for further opportunities. Thank you.

Michael D. Cote

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alternative

the best alternative

set of alternatives

a screened subset of

set of alternatives eliminated through screening

normalization factor for measures

distance between two alternatives for

normalization factor for sub-objectives

distance between two alternatives for

distance between and

value function for

overall goal

number of measures

measure

measure for sub-objective

measure for sub-objective for objective

set of measures

number of elements in

number of alternatives

objective

performance of in

performance of in

number of objectives

a test set of alternatives

number of test set alternatives

distance threshold

set of positive real numbers

sub-objective

sub-objective for objective

adjusted distance threshold

set of sub-objectives

number of sub-objectives

value derived from

total value achieved by an alternative in all measures

vector of an alternative's value achievement in each measure

value derived from

total value achieved by an alternative in all sub-objectives

vector of an alternative's value achievement in each sub-objective

global weight of for

total global weight of

weight vector for measures

global weight of for

total global weight of

weight vector for sub-objectives

size of subset of

acceptable alternatives within the test set

unacceptable alternatives within the test set

ideal alternative; centroid of

an acceptable test alternative

an unacceptable test alternative

Definitions

Goal

The overall goal of a decision problem defines what the decision maker wishes to accomplish. In an evaluative hierarchy, the goal sits alone at the top and can usually be assessed by a maximization or minimization function.

Objective

The set of objectives determines what must be accomplished for the decision maker to meet the goal. Objectives may compete: increased achievement in one objective may come at the cost of decreased achievement in another objective.

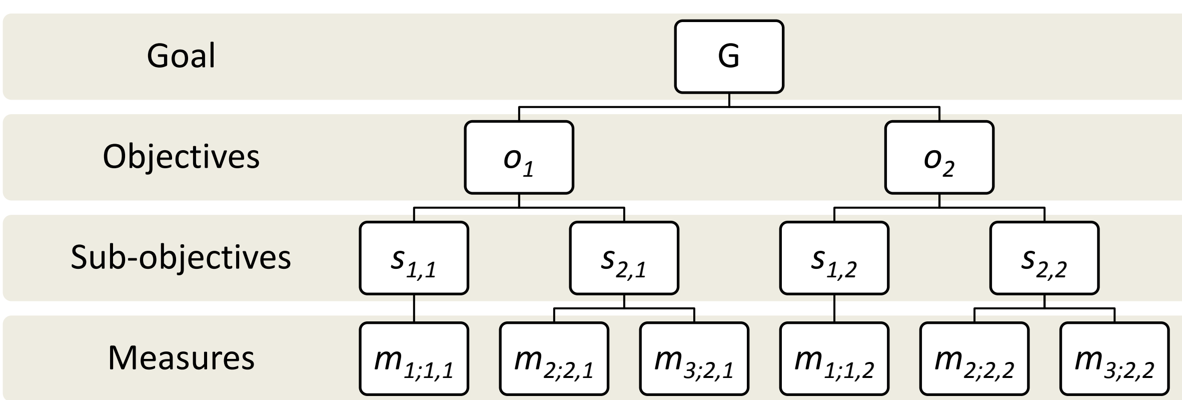
Sub-objective

Sub-objectives separate a single objective into its component parts, to better understand how well an objective is achieved.

Measure

A measure is a performance indicator on which direct data can be obtained. A set of measures is used to determine achievement in a sub-objective. In the literature, the term 'metric' is also commonly used for this bottom level of the hierarchy.

Example hierarchy



SCREENING AND SUFFICIENCY IN MULTIOBJECTIVE DECISION PROBLEMS WITH LARGE ALTERNATIVE SETS

I. Introduction

Complex decision problems require careful study to choose, with confidence, an appropriate solution to meet the overall goal. The job of the analyst is to reduce this complexity to a model that reasonably replicates actuality and adds value to the decision making process. Difficulties can manifest in the problem structure, with competing objectives, or in the solution pool, with many alternatives available. When the solution pool is large, it may be beneficial to eliminate poor alternatives to allow for better examination of the reduced set of alternatives.

I.A. Background

Multicriteria Decision Analysis.

The methods of decision analysis (DA) are implemented to create a framework to objectively analyze a complex decision problem. Input from the decision maker and subject matter experts is used to evaluate how well potential solutions, called alternatives, achieve the overall goal. When a problem features several potentially-competing objectives, multicriteria decision analysis (MCDA) may be used. The purpose of MCDA is to assist the decision maker in sorting alternatives into groups, ranking alternatives in an order, or selecting a best alternative. At a fundamental level, MCDA can be used to eliminate alternatives that do not appear to warrant further attention (Hobbs & Meier, 2000). Screening the alternative set creates a smaller universe of potential solutions, from which an ideal solution may be more easily identified.

While multicriteria decision analysis processes are helpful for many problems, complicating features can exist. Because MCDA requires each alternative to be evaluated

against a hierarchy derived from the decision maker's values and preferences, the analyst must have access to detailed performance data. Determining the performance of each alternative can prove prohibitive in a problem with a very large number of alternatives. A screening process may be helpful to reduce the number of alternatives that must be precisely evaluated.

Identifying and eliminating dominated alternatives that will never prove ideal can reduce the size of the alternative set. The resulting screened set of alternatives, nearly guaranteed to contain the best solution, can then be examined more closely. When the problem under study is to develop an ideal portfolio comprised of several alternatives, screening is especially important due to the combinatorial nature of the number of potential portfolios. A method to reduce the alternative set to a more tractable size is vital.

Combinatorial Difficulties.

Portfolio selection problems featuring alternative sets that grow combinatorially present significant difficulty in computation and evaluation. Consider an alternative set that contains elements. A -combination of set is a subset of elements from . Thus, . The subset may have any number of elements from one to . The number of possible -combinations of is represented by

(1)

where is the number of elements in and , the factorial, is defined as follows:

(2)

When the solution to a problem is a portfolio of alternatives, the size of the portfolio is generally unknown: will one alternative solve the problem, are three needed, are ten needed? Thus, out of the set of potential alternatives to be included in the final portfolio, every size portfolio must be considered. The total number of possible portfolios becomes

(3)

This sum grows rapidly with each new alternative introduced, as shown in Table 1.

Table 1: Combinatorial growth

Alternatives	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*15*	*20*	*30*
Combinations	1	3	7	15	31	63	127	255	511	1023	32767	1048575	1073741823

Thus, if one can eliminate a small number of alternatives, the number of combinations of those alternatives is greatly reduced, as seen in Figure 1.

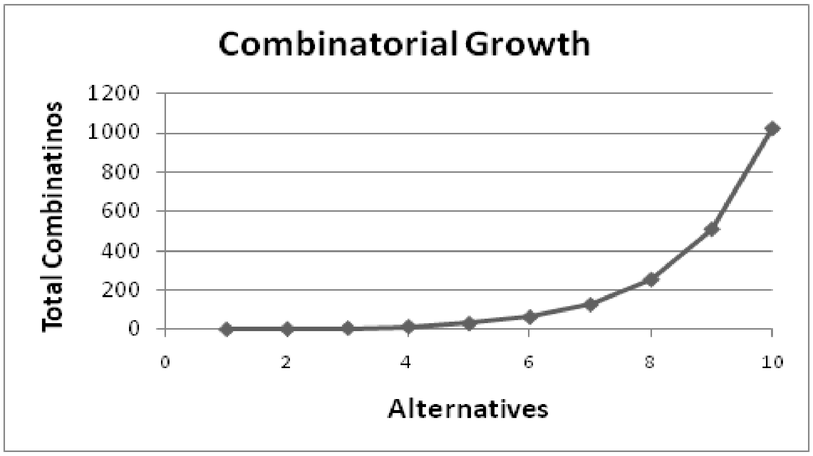


Figure 1: Graph of combinatorial growth

Table 2 illustrates the dramatic reduction in combinations possible.

Table 2: Combination reduction

Size of *n*	% Reduction in Alternatives		% Reduction in Combinations
10	10%		50.05%
	20%		75.07%
	30%		87.59%
20	10%		75.00%
	20%		93.75%
	30%		98.44%
30	10%		87.50%
	20%		98.44%
	30%		99.80%

For a problem with ten alternatives, eliminating one alternative (or ten percent) reduces the number of combinations to be evaluated by over half. On a larger problem with 30 alternatives, eliminating ten percent, just three of the alternatives, reduces the number of

combinations by nearly 88%; eliminating thirty percent of the alternatives reduces the number of combinations by 99.8%. As the size of the alternative pool grows even larger, eliminating a tiny fraction of alternatives drastically reduces the number of portfolios that must be considered.

Screening.

Screening the alternative set to marginally reduce its cardinality can greatly reduce the number of combinations and thereby the time and cost associated with evaluation. When portfolios require complex modeling for performance evaluation, prohibitive computational processing times can result.

Once a decision is made to screen alternatives, it becomes necessary to utilize a proper screening methodology. The analyst must establish appropriate screening factors and determine at what level criteria should be set so that potentially useful alternatives are not mistakenly eliminated. An alternative must provide sufficient performance in supporting objectives to effectively achieve the goal. Defining this sufficiency level allows for appropriate screening -- any solution that is insufficient can be screened out. This sufficiency process applies when one alternative must be selected or when a portfolio of alternatives must perform sufficiently to achieve the goal.

I.B. Problem Statement

Portfolio selection problems with a large number of alternatives can be impossible to precisely evaluate on a reasonable timescale due to both data collection and computation difficulties. Eliminating alternatives through an intelligent screening process can greatly reduce the number of portfolios under consideration. This shortens problem evaluation time and allows for closer examination of the remaining quality portfolios.

In this paper, a method is developed to examine a specific class of problems with very large alternative sets. First, a novel capability-based alternative screening process is devised and progressively applied to several screening situations. Then, a performance-based portfolio screening process is explored to estimate portfolio sufficiency according to the performance requirements of the decision maker. Once a set of sufficient portfolios has been established, the analyst can use higher resolution post-analysis methods to choose a final solution.

I.C. Research Scope

The class of hierarchical problems under study consists of those in which an overall goal is met through achievement in multiple objectives; all objectives are judged on the same set of sub-objectives. However, measures of performance for the sub-objectives are allowed to vary among objectives. The decision maker wishes to select an ideal portfolio of alternatives best to meet the overall goal.

The methodology is most useful when a large number of alternatives produces an extremely large set of possible portfolios, making evaluation of each portfolio's performance impossible. This research develops a two-step process to reduce the number of alternatives for problems of this common structure and then determine which remaining portfolios sufficiently meet the decision maker's requirement.

I.D. Assumptions

The methodology assumes a problem subject to its application can be structured as previously described. Additionally, the performance of alternatives is assumed to be determined through evaluation against a hierarchical model that has been rigorously created through firm DA methodologies.

I.E. Thesis Organization

The remainder of this thesis contains four chapters: Chapter II explores literature in areas pertinent to solving problems of this structure; Chapter III synthesizes concepts from the literature review to develop a methodology for problem analysis; Chapter IV progressively applies the developed methodology to a current problem and analyzes the results; finally, Chapter V discusses relevant conclusions and examines opportunities for further research.

II. Literature Review

II.A Introduction

The purpose of this literature review is to explore thoroughly the areas of sufficiency and alternative screening in multicriteria decision analysis. A brief description of decision analysis will be provided, followed by longer explorations of the aforementioned fields. As these areas are less developed in the literature, a comprehensive examination will be made in an effort to fully understand which elements should be considered for future methodology creation.

II.B Decision Analysis

The field of decision analysis (DA), a subset of the broader field of Operations Research, "provides effective methods for organizing a complex problem into a structure that can be analyzed" (Clemen & Reilly, 2001). Generally, a decision maker must select an alternative that will best solve the problem faced. A best practice to assist the decision maker is to create a hierarchical model of objectives and values according to the philosophy of value focused thinking (VFT). VFT approaches a decision problem by first identifying what needs to be achieved -- the objectives. These objectives are each broken down into what is desirable in an ideal solution -- the values (Clemen & Reilly, 2001). These values are reduced to a set of measureable metrics; potential solutions are generated and then evaluated against these metrics.

VFT is preferred to alternative focused thinking, which simply examines the pre-existing set of alternatives and selects the best among them, thus eliminating the opportunity to identify and explore alternatives not initially considered.

Several desirable properties exist for the value hierarchy developed. The hierarchy should exhibit *completeness*, meaning the evaluation considerations at each tier cover all

concerns necessary for overall objective evaluation. The hierarchy must be *nonredundant*, so that no two evaluation considerations in the same tier overlap. The hierarchy must be *decomposable*, meaning each evaluation criteria is independent of others. The hierarchy should be *operable*, so it is easily understood by anyone who will use it. Finally, it is desirable to have a hierarchy of *small size* while still encapsulating all necessary elements (Kirkwood, 1997). Ideally, the hierarchical model will provide a consistent systematic framework for alternative evaluation and decision justification (Dawley, Marentette, & Long, 2008).

II.C Sufficiency

Many problems ask the fundamental question: "how much is enough?" When evaluating alternatives to achieve a non-binary objective (i.e., there is not an obvious success/fail point), the decision maker generally acknowledges a certain minimum level of accomplishment that is acceptable. Whatever alternative is chosen, it must meet this level to be considered a sufficient solution. Beyond this level, a "better" alternative may provide more value toward meeting the objective. However, any additional resource requirements of this "better" alternative may be too high to justify the marginal increase in value achievement.

The decision maker wishes to maximize performance on an objective or set of objectives while minimizing the resources necessary for that achievement. While this fundamental question of sufficiency is approached in decision problems in diverse fields, little effort has been made to formally investigate how to establish sufficiency.

Military sufficiency.

The military deals frequently with questions of sufficiency in regards to long-term force structure. Because of the lengthy defense acquisition cycle, it is vital to project what may be needed under a variety of circumstances. Since the Cold War, sufficiency has been a key part of

the discussion on deterrence. The United States must have "sufficient military capabilities available to provide a wide range of flexible options for military and non-military conflict" (DuBridge, 1969). This sufficient force must be able to

> deter an attack upon the United States or its allies; respond at a level appropriate to situations short of an all-out attack on the United States; retaliate effectively, after an all-out attack on the United States; and, ensure national survival in the event of an attack. (Temple III, 2005)

In the Cold War environment with memories of Pearl Harbor still fresh, defense sufficiency meant maintaining a force structure with the ability to respond to any and all provocations.

More recently, the United States Navy studied sufficiency in its surface combatant force structure for a 25-year horizon (Morris, 2000). The Navy recognized that traditional wargame modeling techniques based on global war theory are insufficiently broad in scope and incapable of high fidelity modeling, and thus inappropriate to model local warfare and non-military operations. A future force structure needs to perform peacetime missions efficiently but also manage a quick transition to wartime readiness if necessary.

Traditional Cold War-era battle groups are inefficient for joint and asymmetric warfare as standardized groups possess either too little or too much capability. The operating area of a surface combatant was modeled through location of the attack target and the reach of available weapons. Large operating areas enable a single surface combatant to contribute to multiple tasks, which tends to reduce the number of ships needed to perform the whole set of tasks. For example, strategic land-attack missions could be performed with Tomahawk missiles from almost any ship in the theatre, but for all other tasks the assigned ships would have to be near the asset being defended or attacked (Morris, 2000).

The Johns Hopkins Applied Physics Laboratory developed a 'sufficiency analysis' methodology to determine the types and numbers of assets needed to perform a task. The process decomposed a complex multi-area warfare problem into a set of single-area problems, solved these simpler problems, then integrated the results to obtain a solution. Success criteria determined whether a set of surface combatants was able to accomplish a task at an acceptable level of risk. These criteria were defined by quantifiable measures of effectiveness (MOE) with threshold values assigned for each measure. The risk for a task was deemed acceptable if and only if all MOEs exceeded the thresholds; typical MOE thresholds were 0.9 in terms of probability of success.

One method used to set these thresholds was to find the point of diminishing return -- the "knee" on the curve of effectiveness versus number of assets dedicated to a task. This did not account for failure consequence severity or attack likelihood, so a Naval subject matter expert used professional judgment to determine the amount of risk considered acceptable. The study concluded that a surface force mixture should consist of fewer, highly-capable ships as opposed to a larger number of less-capable ships, as overall force size could be minimized while capability could be maximized when a preponderance of the force consisted of the very best ships. The concept of sufficiency of force was developed through combining known capabilities with subject matter expert opinions on risk and future needs.

General sufficiency theory.

Advances in technology and changes in the international political landscape have transformed the role of the analyst. Frequently, a decision must be made when it is unknown whether there are enough pieces of information or if the information available is of high enough quality to make a good decision. The decision maker is subject to the "supervisor's dilemma",

defined as "a generic situation wherein a supervisor must decide if the output product of an analysis is acceptably rigorous or if more analytical resources must be invested in that analysis process before sending it forward" (Zelik, Woods, & Patterson, 2009). The decision maker wishes to know if the data available and analysis performed is sufficient to move ahead with the decision making process.

Zelik et al. develop an approach to determine analysis sufficiency based on rigor of process as an indicator of information sufficiency. "Given the current analytical production pressures and the technology driven proliferation of data availability shaping the intelligence community, it's increasingly difficult to accurately judge the sufficiency of an analysis" (Zelik, Patterson, & Woods, 2007). To adapt to these changes, improvement in the understanding of the analytical process was investigated. Analysis sufficiency is judged on the basis of rigor in the analytical process. "Rigor, as an assessment of process quality, is used in information analysis to communicate about the process, rather than the product, of analysis" (Zelik, Patterson, & Woods, 2007).

It is difficult to know when sufficient data analysis has been performed. By adhering to an accepted and rigorous analytical process, one can feel confident in the level of analysis. Achieving 'maximum' rigor of process is not a goal; rather, one should continually adapt the process of analysis to changes in the world to ensure the analysis is rigorous enough. The supervisor's dilemma captures the fundamental tradeoffs inherent in analysis work, by balancing urgency and limited resources against the need to perform broad research to gain insight.

By presenting a subject pool of analysts and decision makers to the structure of an analysis (not the actual analysis itself), Zelik et al. attempted to gain an understanding of how process influences quality. The data indicate that providing insight into an analysis process

influences assessments of both process rigor and product quality. Participants made insightful comments about the quality of an analytic process based on product quality, but these perceptions were apt to change with the addition of process insight. This distinguishes perceived rigor, based on cues inferred from an analytic product, from effective rigor, based on insight into the analytic process; these two areas may not always be aligned. Subject responses demonstrated there is no one right way to perform analysis. Different practices can produce acceptable results, and approaches can be valid even if not completely understood.

This examination of process as a measuring stick for analysis sufficiency helps prevent overconfidence in inadequate analysis (and likewise underconfidence in strong analysis). Such overconfidence in superficially-adept analysis can lead to catastrophic results. The investigation into the loss of the space shuttle Columbia showed that critical decisions were made based on analyses that appeared to be thorough but was in reality of low rigor. Using the strength of analysis as a proxy for product quality advances the true goal of the analytic effort -- not providing individual facts or reports, but providing information and understanding in a meaningful context (Zelik, Patterson, & Woods, 2007).

The supervisor's dilemma does not advocate 'maximum' rigor, it concerns determining what is sufficient rigor when balancing in the costs of further work. In this sense, dedicating further resources to a problem -- resources that could be allocated elsewhere -- can actually *decrease* the value of that research. The theory of "just barely good enough" (JBGE) in agile modeling and computer programming suggests that time and effort spent above and beyond the minimum requirement adds little extra functionality to the solution and decreases the overall value of the product as the cost to capability ratio increases. The JBGE model, by including the cost of a solution in the overall understanding of "value" obtained, presents the most efficient

solution possible. It does not imply low quality, as the threshold for sufficiency is set at what is acceptable. The point when JBGE is reached is situational and dynamic as needs change, and generally comes sooner than expected (Ambler S. , 2002).

If a model or solution must meet a pre-determined requirement, then once it hits that sufficiency level -- once it is *good enough* for effective use -- then anything beyond that is a waste of time or money. The point of diminishing returns has been reached; further capability might be added, but it is not necessary and comes at a higher cost than minimum development, thereby decreasing overall value. The graph of value of performance when cost is considered as a function of effort, shown in Figure 2, is not a monotonically increasing function but a parabola with the local maxima representing the JBGE point. This point achieves the highest possible value as a function of cost, as any less effort produces insufficient capability, while any more effort produces more, unneeded capability, at a higher cost that diminishes overall return.

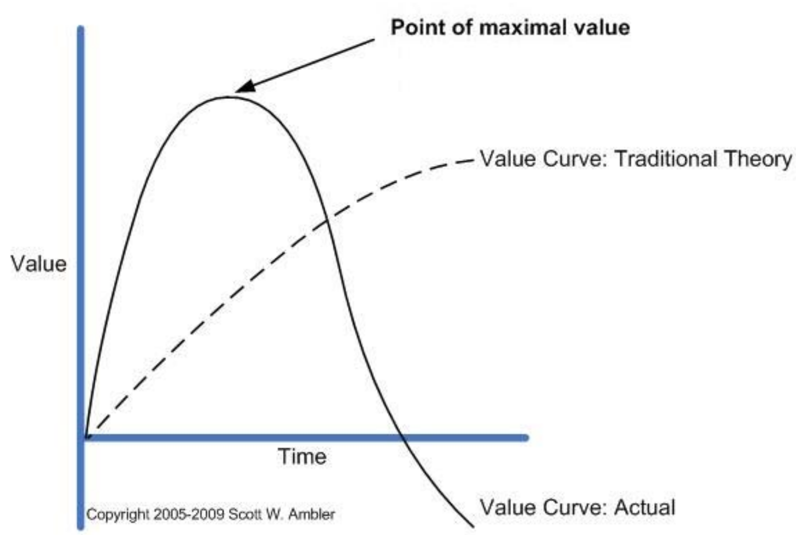


Figure 2: Just barely good enough (Ambler S. W., 2009)

Three key tenants must be followed with respect to this theory. First, JBGE is situational, in that what defines 'good enough' changes based on the ultimate needs both now and in the future. The point of JBGE may shift as demands change. Re-working a product to meet a less complex requirement is wasted time, unless the current version decreases value elsewhere, as may be the case when the model is used to determine data analysis needs.

Second, any requirement must be clearly agreed upon by the analyst and the user/decision maker, so that the product is good enough to function and that effort is not wasted on functionality that will not be used. Finally, and most importantly, the point of JBGE comes quicker than expected, as the value in modeling "comes through improved communication and ability to think things through, and that this value peaks rather quickly" (Ambler S. W., 2009). Human nature is to err on the conservative side, but this must be avoided as not to waste resources. Development should aim for sufficiency.

Sufficiency in fields of study.

Though the literature contains limited investigation into the theory of sufficiency in data analysis, concepts of sufficiency in application to a specific field are discussed more prominently. Much research has been devoted to the concept of a sufficient statistic -- a statistic which has the property of sufficiency with respect to a statistical model and its associated unknown parameter, such that "no other statistic which can be calculated from the same sample provides any additional information as to the value of the parameter to be estimated" (Fisher, 1922). Most commonly used in regards to discovering an underlying distribution, a statistic is sufficient if the sample from which it is calculated gives no additional information than does the statistic.

An example of this application is determining how much data is necessary to be confident in the distribution of a population of unknown size. Veres et al. studied sufficiency in biometric data collection, estimating how many subjects are needed to cover diversity of population in gait and how many samples per subject are needed to provide representation of the similarities and differences in the gait of a single subject. Their investigation into when the data is sufficient to have statistically significant results for chosen values of Type 1 and Type 2 error reinforces the concept of diminishing returns on data collection. After some population size, the number of subjects needed to characterize that population stays practically the same, and there is almost no value in expending resources to collect further data (Veres, Nixon, & Carter, 2006).

A similar question of how much data is sufficient to determine an underlying trend is found in the analysis of physician performance. Measuring the true quality of physician performance is important to a range of healthcare initiatives. Most tools use a performance ratio based on the number of patients with the diagnosis of interest, with a minimum number of patients needed to establish a valid physician score. For a single performance measure with a high level of unreliability, as many as 100 patients with a particular condition might be necessary to measure a physician's performance (Lumetra, 2005).

However, the amount of data needed can be reduced by using a composite score, combining performance results across multiple single indicators of performance. Such aggregated measures reduce the unreliability in the measurement and thus the number of patients with a particular medical condition needed. As few as 25 patients per doctor may be enough to compute performance measures that accurately discriminate performance among providers. The key is to use the right mix of data sources, which is unique to each problem. Combining different *types* of data, each with a different reliability level, can provide a clearer picture than a

larger amount of a single type of data. It may be possible to more quickly gain insight into the characteristics of the subject of study through the use of less, but aggregated, data.

The use of less data than is expected to be necessary is important to resource conservation. Monitoring traffic system intersections to determine real-time flow distributions requires significant resource investment, as "control systems are often hungry for extensive detector information from a rich detector configuration" (Lan, 2001). Lower levels of information may be sufficient for the control system to perform its task. Reducing the collectors needed to determine system behavior in one area allows for additional information to be gathered elsewhere, increasing overall system knowledge.

Lan investigated how partial sets of detectors provide less, yet still sufficient, information, albeit with the penalty of less accuracy and greater variability. In a simple three-way intersection example, a configuration with five detectors instead of six can still provide necessary and sufficient data for system control. More generally, testing on the Jacobian matrix of the predicted parameter outputs of traffic count at an intersection can determine whether a detector configuration can provide sufficient information for flow estimation. With this method, "as long as one can generate an *a priori* reasonable set of input counts, no actual data are needed to perform [the analysis]" (Lan, 2001). The capabilities of the system can be examined based solely on its own properties, without the need for exact performance data.

In the traffic example, a set of detectors must continually monitor the changing status of the system. The field of change point analysis provides techniques to determine when an abrupt change in state occurs. Discovering when a party of interest makes a change is vital to intelligence gathering. For example, an enemy base may store a certain number of tanks -- this is

the default state. When the tanks are no longer at the base, the state has changed, and the analyst can then try to determine where the tanks went and what this may mean in the larger scheme.

In such situations, change point theory may be applied. Commonly used in industrial quality control, change point detection (also known as statistical process control) is used to continuously monitor a process and determine when an underlying distribution has changed. Consider a manufacturing plant manager who is interested in detecting when the quality of the product has decreased. While a single observation can be used (i.e., a certain measurement on a widget must be within a tolerance to meet the specification), it is also possible to observe a process through multiple data streams. This multivariate surveillance is useful if any number of potential changes to different parts of a system can indicate a change point. A surveillance procedure should have a high probability of detecting a change within a reasonable period of time, with a low probability of false alarm (Wessman, 1998).

If dense data streams are monitored automatically, an alarm procedure must be developed to identify the change point. This can be done through a univariate process based on a summarizing statistic, or analysis of the separately-monitored component processes. Wessman explored a likelihood ratio-based surveillance procedure in processes where a sudden shift occurs between two fully-specified alternatives that is reflected in all component processes. In a multivariate manufacturing example, the physical breakdown of a machine or machine part would cause a number of observable data distributions to suddenly change. In an intelligence situation, a large shift in enemy equipment would result in a change to the "distribution" of the expected observation.

Wessman examined sufficient reductions to change detection methods that do not suffer from significant loss of efficiency. For processes where the change is between two fully

specified alternatives, when the change points from multiple intelligence streams occur simultaneously, a univariate likelihood ratio statistic method is sufficient for detecting certain critical events. Correspondingly, a good surveillance procedure can utilize this univariate process.

Interest in continual statistical surveillance with regards to intelligence gathering has increased in recent years, with the aim of determining when an important change in an underlying process has occurred (Frisen, Andersson, & Schioler, 2009). This type of surveillance involves collecting data from several related variables, calling for multivariate surveillance techniques. Optimality in terms of data collection is hard to derive and even hard to define in such multivariate problems. It is possible that multivariate surveillance problems can be simplified by the sufficiency principle, which states that all conclusions to be drawn should depend only on a sufficient statistic.

In intelligence surveillance there is the potential for complex relations between change points, ranging from simultaneous changes to independent changes. One method for simplification is to reduce the variate vector into one statistic and then use a system for univariate surveillance on this statistic. Monitoring each variable separately, in a combined univariate method, is also possible. A common method to combine the information is to signal the alarm at the first time that any of the univariate methods gives an alarm (Frisen, Andersson, & Schioler, 2009). In a situation where only one process changes, the performance is considerably improved if this knowledge is utilized in the surveillance procedure.

II.D Alternative Screening

Once sufficiency requirements for a set of alternatives have been determined, the set should be screened to isolate quality alternatives. Screening criteria are used, each of which

"consists of an attribute and a cutoff level which divide areas [alternatives] into those which are acceptable and those which are not" (Keeney, 1980).

Belton and Stewart (2003) state that "sometimes the problem is not one of generating alternatives, but one of identifying an appropriate and manageable set for detailed evaluation from a much larger set of possibilities -- a screening process." The set should be made up of "good" alternatives, or alternatives which represent the range of possibilities. Strategies to accomplish this include bounding the space of promising alternatives, or using a simplified assessment model.

Chen (2006) observes that "during the past few decades several different methods have been separately put forward to deal with screening problems. But there has been no systematic exploration of this topic in the literature, and researchers on sorting [ordering solutions] have paid little attention to it." Similar to sufficiency theory in data analysis, there has been little advanced investigation into how screening criteria should be established. Instead, general guidelines for screening advocate caution.

Performance screening.

Various options for screening on alternative performance are available. The following is a partial list developed by the National Institute of Standards and Technology. For each of these screening methods, the threshold levels are set by subject matter experts.

> *Dominance*
> An alternative is dominated if another alternative out-performs it with respect to at least one attribute, and performs [at least] equally with respect to the remainder of attributes. With the Dominance method, alternatives are screened such that all dominated alternatives are discarded. The screening power of this method tends to decrease as the number of independent attributes becomes larger.
>
> *Conjunctive ("Satisficing")*
> The Conjunctive method is purely a screening method. The requirement embodied by the Conjunctive screening approach is that in order to be acceptable,

an alternative must exceed given performance thresholds for *all* attributes. The attributes (and thus the thresholds) need not be measured in commensurate units.

Disjunctive
The Disjunctive method is also purely a screening method. It is the complement of the Conjunctive method, substituting "or" in place of "and." That is, to pass the Disjunctive screening test, an alternative must exceed the given performance threshold for at *least one* attribute. Like the Conjunctive method, the Disjunctive method does not require attributes to be measured in commensurate units.

Lexicographic
Using this method, attributes are rank-ordered in terms of importance. The alternative with the best performance on the most important attribute is chosen. If there are ties with respect to this attribute, the next most important attribute is considered, and so on. (Norris & Marshall, 1995)

Given the lack of direction in screening theory, many multicriteria decision problems utilize rudimentary screening techniques to conservatively eliminate undesirable alternatives.

In the field of mineral extraction, a company must make a binary decision whether to drill for ore. This decision is based on data indicating if the lode is large enough and of sufficient quality to invest significant resources. Verma (2001) investigated the application of fuzzy logic in mineral resource evaluation. Screening criteria were established for mineral quality measures of performance, then instead of crisp cutoffs, a fuzzy logic process for combining measures was used. Measure sensitivity analysis allowed for more rigorous determination of the sufficiency of the deposit for drilling.

The United States Forest Service (1999), while developing a monitoring program for the environmental health of forests in the Northwest, suggested the following criteria for measures used for screening:

- the dynamics of the measure parallel the larger system

- the measure shows a short-term but persistent response to change in the status of the system

- measure can be accurately and precisely estimated (high signal-to-noise ratio)
- likelihood of detecting a change in the measure performance is high, given a true system change
- low natural variability, and changes in measure values can be distinguished from background variation
- cost of measure obtainment is not prohibitive

While not all of these characteristics will apply to each screening problem, the Forest Service emphasizes that measures should be good reflections of the alternatives they are measuring, especially when used for screening.

Feasibility screening.

The previous section discussed screening methods based on alternative performance. Another option is feasibility screening -- the United States Department of the Interior Bureau of Reclamation advocates only eliminating alternatives that are impossible, as anything that is possible must have its effort of implementation evaluated as part of its scoring. If a possible alternative is eliminated because it seems too difficult prior to a full evaluation, a solution may be missed. Only options with "fatal flaws" should be eliminated (Reclamation's Decision Process Guide).

If an alternative (or set of alternatives) is capable of providing value, then it should not be eliminated. Parnell et al. state:

> Screening criteria should avoid targeting feasible but less desirable alternatives. Feasibility screening sifts out alternatives based on non-negotiable criteria. For all others, finding the best trade-offs will lead to the perfect solution…. All feasible alternatives become solution candidates. Balancing trade-offs to find the preferred solution is accomplished by enhancing and measuring solution candidates. (2008)

Screening criteria should not be so strict that sufficient but superficially undesirable alternatives are eliminated. Determining which alternatives are undesirable is the task of performance screening. By eliminating alternatives prematurely, the power of the process is reduced.

This leads to the question of how "non-negotiable" is defined, and how such criteria should be established. These absolute criteria are established by real-world limitations for the problem at hand and the firm demands of the subject matter experts consulting on the problem. Parnell suggests screening should be done at the 'needs' level, not at the 'wants' or 'desires' level. Screening criteria should be used to ensure solutions meet minimum requirements. These criteria can then be consulted as alternatives are designed, modeled and analyzed. Belton and Stewart state that any such process should:

> screen alternatives in order to exclude ones which are 'non-compliant' in that they do not meet certain minimum specifications. This should always be done with care, making sure that a degree of non-compliance on one criterion could not be compensated for by exceptional performance elsewhere. (2003)

It is warned not to screen on individual measures when overall alternative performance can be improved by success in other measures. Belton and Stewart advocate using a subject matter expert panel to create screening criteria to reduce the alternatives to a smaller set, of which the ideal solution probably exists.

Keeney (1980) advocates using a two-step process, in which absolute requirements dictate screening criteria. Once alternatives have been screened for feasibility, a set of evaluation criteria are developed. Each alternative is then scored against the evaluation criteria for sorting. The initial screening criteria, generated by real-world limitations, eliminate options. The evaluation criteria, developed by subject matter experts, are used to sort alternatives relative to each other.

Definitions.

Chen et al. (2008) performed research on screening in multiple criteria decision analysis, screening alternatives in multiple criteria subset selection, and distance methods for multiple criteria decision aid. Their work provides techniques to reduce the number of alternatives in multiple criteria subset selection problems, thereby making it less difficult to find a good portfolio. The main objective of screening is to remove inferior alternatives from the set of available alternatives, so that those remaining can be investigated in more detail, using more accurate data or more refined assessment criteria.

When utilizing preference expressions on values and weights to form a decision support system, resulting alternatives may be similar. Caution should be used, as screening should provide the decision maker a range of options that emphasize different attributes. The analyst should be careful not to "stack the deck" in favor of a particular set of values, nor yield a set of options that are essentially similar (Chen, Kilgour, & Hipel, 2008).

In a MCDA problem there exist a number of alternatives , the complete set of which is identified by

(4)

Alternatives are evaluated against each metric, or measure, ; the group of measures comprises

(5)

The performance of an alternative for a measure is represented by , as shown in Table 3.

Table 3: Performance matrix

The decision maker may value increasing an alternative's measure performance until a point is reached when little additional value is created. A low level of performance in a measure may have very little value to the decision maker; value would be achieved only when a rough threshold is cleared. The true value of an alternative's performance in a measure is not always a linear function, and is expressed as:

(6)

where the value of the performance is determined by the value function established by the decision maker. The value vector of an alternative's performance in the set of measures is represented by:

(7)

Different measures may have different levels of importance to the decision maker. Thus, it is necessary to assign a global weight to each measure . Weights are non-negative and sum to one:

(8)

(9)

with the weight vector .

In the basic case, once the measure performance and values have been evaluated, the aggregate value score for an alternative, , is calculated:

(10)

Once the value scores for each alternative are derived, the decision making can begin: choosing the best alternative, ranking the alternatives, or sorting the alternatives into groups (Chen, Kilgour, & Hipel, 2008).

Screening, the next analytical step, selects a non-empty subset of (defined as **)** that hopefully contains the ideal solution, .

(11)

(12)

The set of alternatives eliminated by a screening procedure is represented by :

(13)

The process of screening is represented pictorially in Figure 3.

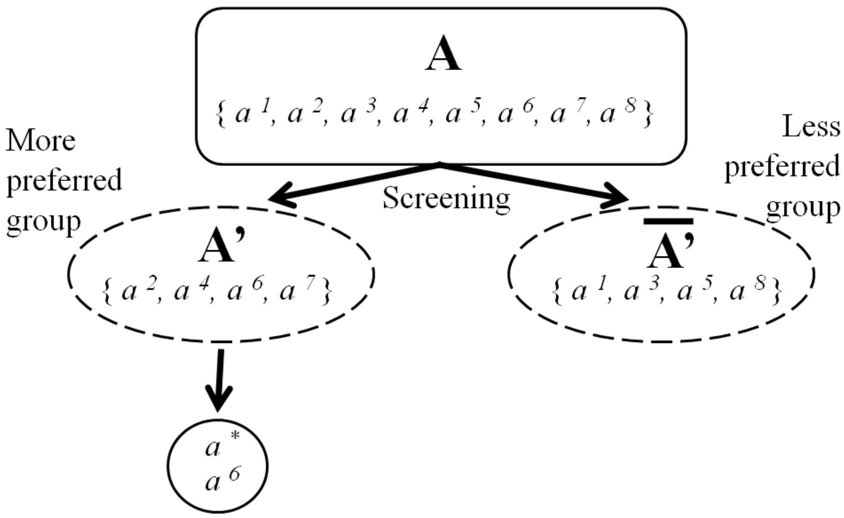


Figure 3: Screening schematic (Chen, Kilgour, & Hipel, 2008)

For a sorting screening procedure, when alternatives are divided into two (or more) preference groups, only preferences between groups can be made, not between alternatives within the same group.

(14)

(15)

where is defined as is preferred over , and is defined as is neither more or less preferred than .

Screening eliminates poor alternatives to allow further analysis to focus on quality alternatives. A screening process should possess three characteristics: safety, efficiency, and good information.

A screening procedure is safe *iff*:

(16)

A safe screening procedure ensures the ideal choice remains in the screened set.

Given two safe screening procedures and , is more efficient than if . The more information the decision maker provides, the more alternatives can be eliminated. Thus, screening procedure must be based on better information than screening procedure .

When an initial screen is insufficient for the decision maker, Chen et al. (2008) advocate the sequential use of various screening methods to arrive at a subset of alternatives for further examination.

Kilgour et al.(2004) explore subset selection knapsack problems. Current screening techniques are poorly suited for subset selection problems as they can eliminate choices that, when combined with other alternatives, would produce the best possible subset. In a resource-constrained knapsack problem, not all individually dominated alternatives can be safely removed from consideration. However, several conditions exist in which a dominated alternative cannot possibly belong to an optimal subset. Without constraints, the problem simply becomes an *m*-

best alternative problem. Finally, sensitivity analysis on weightings should be conducted so alternatives are not eliminated that belong to an ideal subset under slightly different conditions.

Dominance can be used for screening. If an alternative is worse than another alternative in all performance or capability measures, then depending on the problem type the dominated alternative can be discarded (Kilgour, Rajabi, Hipel, & Chen, 2004).

(17)

Distance method.

Chen et al. developed a case-based distance method to screen alternatives. Obtaining accurate decision maker preference on weights and values can be difficult, so this method discards that process. Instead, a test set of alternatives is presented to the decision maker who chooses which subset of the test set is acceptable. This test set may include real past decisions, fictitious but realistic alternatives, and a representative subset of familiar alternatives.

A test set must contain alternatives that mirror all aspects of the real alternatives under consideration, including identical measures. The distance method proposed by Chen et al. (2008) suggests that the acceptable alternatives should be 'close together', while the unacceptable alternatives should be 'outside' such that:

(18)

(19)

Thus,

(20)

(21)

The test set is used to estimate the measure weights , as well as a distance threshold The normalized distance of the alternatives in from the ideal (and imaginary) center of is less than , while the normalized distance of the alternatives in is greater than

Using the weighting developed from this test set, a distance-based screening procedure is used to evaluate the real alternatives in . Alternatives within a certain distance of the imaginary ideal alternative , the centroid of , are selected for further analysis. With and , the measure performance of the ideal alternative is determined by:

— (22)

With the properties of calculated, a weighted squared Euclidian method provides distance information. For all , the normalization factor is defined as:

(23)

Thus, the distance between and for is:

(24)

and the distance between and for is

(25)

The total distance between and is

(26)

Here, is calculated using an optimization procedure (Chen, Kilgour, & Hipel, 2008). However, if weights are known from the decision maker, these can be used instead. Similarly, if the decision maker can outline a true perfect alternative, its measure performance can be used in lieu of the centroid of . Applying the distance procedure to the set of real alternatives, the total distance between and is

(27)

and

(28)

The distance threshold is also calculated from the optimization procedure, and is derived from , the set of acceptable test alternatives. Alternatively, can be adjusted to by the decision maker to reduce or expand to an acceptable level. The screened set is defined by:

(29)

When using a distance method, screening procedure is more efficient than screening procedure if the subset of alternatives produced by is contained within the subset produced by . The screening procedure that produces the smallest safe subset is deemed efficient. This distance based screening procedure is illustrated in Figure 4.

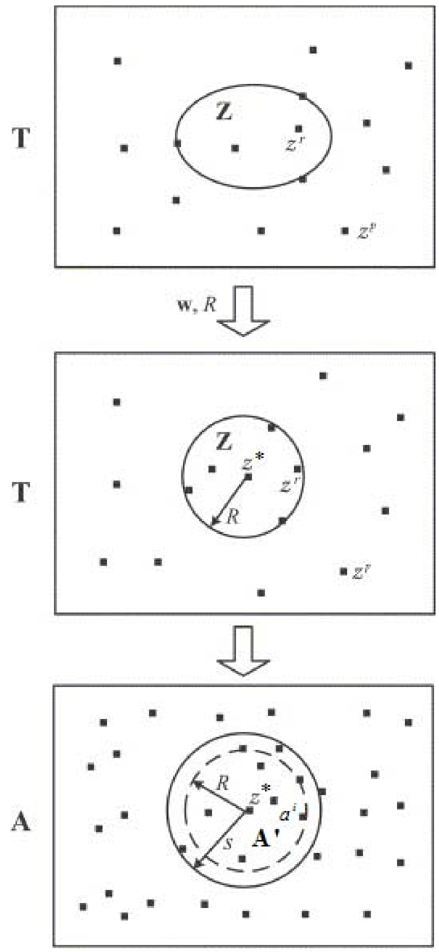


Figure 4: Case based distance method screening procedure (Chen, Kilgour, & Hipel, 2008)

II.E Summary

This chapter presented first a brief review of the concepts of decision analysis and value focused thinking. Further discussion on these areas can be found in the cited materials. A deeper exploration was then made of sufficiency and alternative screening.

The literature strongly suggests sufficiency to be defined by those familiar with the problem, including the decision maker and subject matter experts. Defining the level of performance sufficiency is important, as any effort beyond the requirement may be a waste of resources. Several studies have found sufficiency may be reached with less data than expected.

Regarding military sufficiency, it is important to account for all possible scenarios to ensure flexibility and readiness.

Previous research advises caution when screening and sorting. Performance screening should be conservative, as not to eliminate potentially-good alternatives if conditions change. Many advocate eliminating only impossible solutions, defined by laws of nature or strict decision maker policy.

The next chapter combines the screening and sufficiency concepts discussed in the literature with Chen's distance-based procedure to develop a methodology for alternative screening and sufficiency evaluation in hierarchical problems with large alternative sets.

III. Methodology

III.A. Introduction

This chapter extends the definition of the problem type under consideration and develops a capability-based method for initial alternative screening. Additionally, a method is described to establish portfolio sufficiency levels, allowing for performance-based portfolio screening.

III.B Problem Description

Complex decision problems can demand achievement in a large number of objectives to satisfy an overall goal. In many situations, these objectives, which may be competing, are judged on the same core criteria. Within each objective the criteria, or sub-objectives, may have varying importance. A potential solution is then evaluated on these sub-objectives to determine how well it meets the objectives and thus the goal. When a large alternative set exists, the problem can easily grow too large to precisely evaluate all alternatives or combinations of alternatives, either from a data collection or computation standpoint. In situations such as this, it is beneficial to trim the number of alternatives to a more manageable set. This smaller set of quality alternatives can then be examined more closely.

Consider a company that wishes to achieve internal control over its transportation needs. The chosen strategy is to procure a fleet of vehicles that fulfills a variety of needs: long haul transportation of goods, local transportation of goods, executive transportation, etc. Each of these need domains represents an objective for the company; an appropriate solution will procure enough vehicles of different types to meet all objectives and thus meet the overall goal of transportation control. Notably, these objectives compete: a vehicle that is effective at long haul

transportation of goods is poor at executive transportation. Two of these objectives, for simplicity given equal importance, are shown in Figure 5.

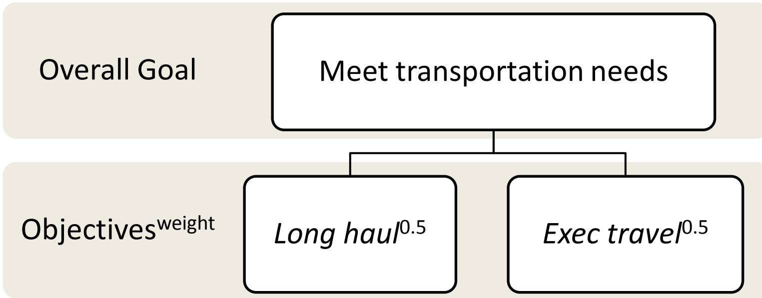


Figure 5: Company trasportation objectives

Any vehicle could theoretically achieve some level of value in each objective (even if that value is very close to zero). As such, each objective is evaluated on the same set of vehicle capability sub-objectives. A sample of sub-objectives used to determine objective achievement may be: highway performance (HP), goods capacity (Cap), and passenger comfort (Comf). However, as objective requirements vary widely, the sub-objectives under each objective are weighted differently, as seen in the superscripts. Figure 6 expands on the Figure 5 hierarchy by adding three evaluative sub-objectives under each objective.

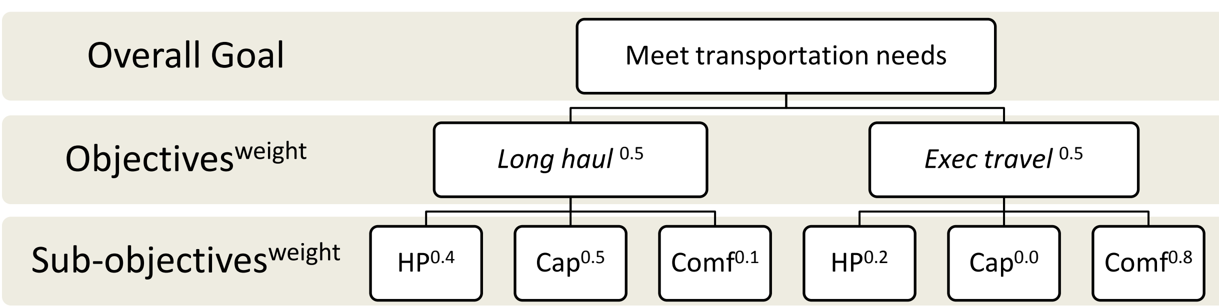


Figure 6: Identical sub-objectives define each objective

Achievement in a sub-objective is determined by value obtained in set of associated performance measures. Data is gathered directly on the performance measures. In this example, highway performance is measured through cost per mile traveled (CPM). Capacity is measured in two parts: goods capacity and people capacity. Comfort is measured through the amenities available to a passenger. Measures may be categorical; with comfort, increasing value is assigned to escalating luxury level. The updated performance hierarchy is shown in Figure 7.

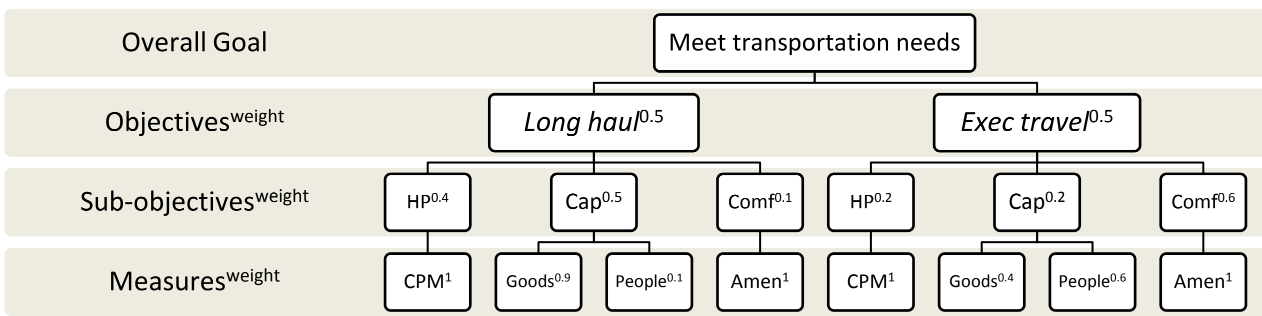


Figure 7: Performance measures determine sub-objective value achievement

The vehicles available for purchase are the alternatives. The company can select a portfolio of vehicles that best meets its transportation needs by evaluating each possible portfolio against the performance hierarchy. As there are hundreds of vehicles on the market to choose from, there exists a very large number of possible portfolios. Eliminating some of these vehicles from consideration will reduce the number of possible portfolios and allow for more manageable evaluation.

III.C Hierarchy Consolidation

Background.

This problem is currently structured with a *performance-based* hierarchy. The standard evaluation method is to gather precise performance data across all measures for all alternatives. If the number of alternatives is very large, this data may be difficult or even impossible to obtain. When the solution involves selecting a portfolio, each of which requires evaluation against the hierarchy, the combinatorial nature of evaluating all possible alternative combinations becomes prohibitive. To use the hierarchy at a later time, alternative performance data must be updated, requiring significant recollection cost.

To combat this difficulty, the problem structure can be transformed from a *performance-based* hierarchy to a *capability-based* hierarchy. As the sub-objectives are the same for each objective, the sub-objective local weights can be transformed into global weights and summed, thus determining which sub-objectives are most important to the overall goal. Then, the large multi-objective performance-based hierarchy is reduced to a capability-based hierarchy featuring only sub-objectives. To determine their potential contribution to the overall goal, alternatives can be rated on a binary capability scale of whether they contribute to a sub-objective, and true performance data (which may be difficult or impossible to gather) can be ignored. Sub-objective value functions or even exact measures of performance are no longer necessary, greatly eliminating data collection costs. In this way, alternatives that offer high capability can be identified as likely to be included in a good portfolio.

Approach.

A decision problem can be structured in three different ways. The decision maker can be tasked with i) selecting the best alternative from the set , ii) sorting into different groups

that are arranged in a preference order, and iii) ranking the alternatives of from best to worst (Chen, Kilgour, Hipel 2004).

The procedure presented here focuses on the second structure, specifically sorting the alternatives in into two groups -- one selected for further examination and one to be eliminated . This will be accomplished by evaluating alternatives on the new capability-based hierarchy. This approach can be used on problems where the sub-objectives are identical for a set of objectives and alternative capability (if an alternative is designed to exhibit a specific capability) is understood.

True alternative *performance* for a capability is not necessary, nor is a value function relating that performance into sub-objective value achievement. In this procedure, sub-objective and measure weights are known via subject matter experts and/or the decision maker, as is the performance of an imaginary ideal alternative. Both of these pieces of information are generally easily obtained; if necessary, this information can be obtained indirectly using the method of Chen et al., a linear programming optimization procedure using alternative test sets.

Procedure.

A multi-criteria decision analysis problem is explored in which a series of top objectives are all evaluated on the same set of sub-objectives . Each objective is distinct, yet the underlying hierarchy is repeated, as shown in Figure 8. The performance measures may be evaluated differently among the sub-objectives, as appropriate and needed.

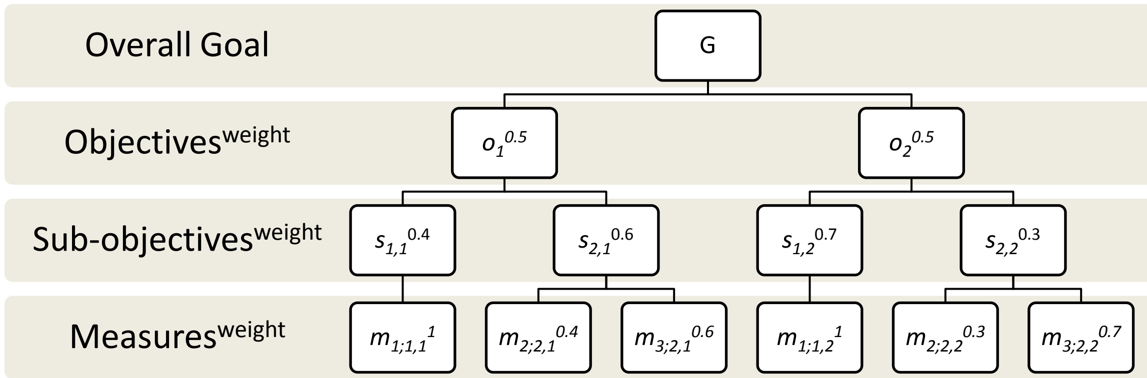


Figure 8: Full performance-based hierarchy

While the sub-objectives are the same for each objective, they may possess different importance depending on the objective, and thus are assigned appropriate local weights. The objectives can have different importance to the overall goal, but for simplicity here they are all of equal weight. This is a small performance-based hierarchy with only two objectives; a complex multiobjective decision analysis problem may have over ten objectives, generating dozens of sub-objectives and potentially hundreds of measures. If perhaps 20 alternatives are under consideration, data for thousands of performance measures must be gathered. This would require significant resource allocation for the initial evaluation; any future change in performance measures or alternative capability would require additional data collection. Most importantly, evaluating every combination of the 20 alternatives against the entire hierarchy would demand significant time and resources.

It is necessary to reduce the performance-based hierarchy to a capability-based hierarchy. To do this, the measures are ignored while the sub-objectives are featured. The sub-objective local weights are transformed to global weights, as shown in Figure 9.

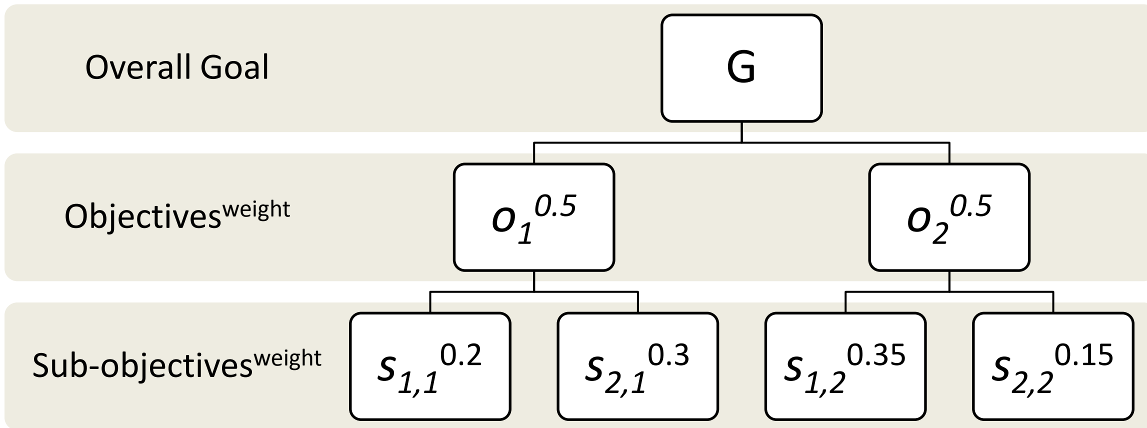


Figure 9: Elimination of performance measures

In the example shown in Figure 9, , and , the number of distinct sub-objectives. The goal of this transformation is to determine which of the sub-objectives are most important. It follows that alternatives that provide that capability in the important sub-objectives are highly desirable. Here, is the total global weight of , while is the global weight of . There are objectives.

(30)

(31)

The vector provides the relative importance of the sub-objectives towards meeting the entire set of objects. This creates the capability-based hierarchy seen in Figure 10.

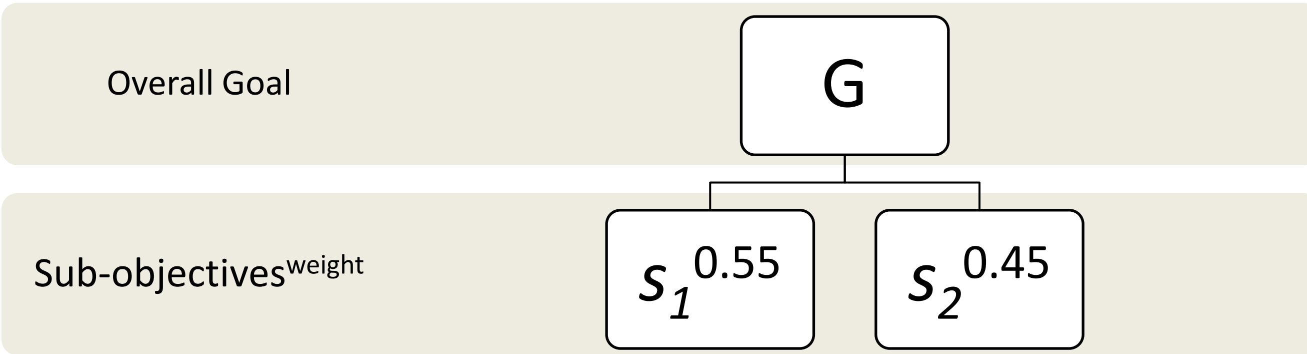


Figure 10: Capability-based hierarchy

Now, an alternative is evaluated directly on the sub-objectives -- specifically, if it is designed to provide a capability. If yes, then the alternative scores a "1" for that sub-objective; if not, the alternative scores a "0." Instead of a number of precise performance measure data points for each alternative, only knowledge of whether that alternative is designed to achieve capability in a sub-objective is needed. Evaluating each alternative against the reduced hierarchy allows for to be screened into and , with size of each according to the rigor required by the decision maker.

III.D Alternative Screening

Once a large performance-based hierarchy is converted to a capability-based hierarchy, a modified distance method can be used to screen the alternative set. As previously described, , the set of alternatives considered. Alternatives are evaluated against each sub-objective in the reduced capability-based hierarchy. The group of sub-objectives comprises .

In this methodology, an alternative is evaluated simply on whether it is designed to provide a capability in a sub-objective. Measure performance and resulting measure value become obsolete. Instead, an alternative's performance in a sub-objective, defined as ,

is based purely on capability, and becomes a binary 0 or 1 response. Thus, the value an alternative achieves for that capability in a sub-objective, defined as , is also a binary response. The set of values for the sub-objective capabilities of alternative is represented by , a string of 0s and 1s.

As different sub-objectives may have different levels of importance to the decision maker, the reduction procedure changes local weights (assigned by subject matter experts) to global weights for each sub-objective , with and the weight vector .

Once alternatives are scored against the capability-based hierarchy, various screening procedures can be assessed. In a basic approach, one could screen based on total value to keep a certain number of alternatives that provide the highest independent capability. Or, one can remove dominated alternatives. For example, if an alternative provides capability in a certain set of sub-objectives but there exists another alternative that provides those same capabilities plus more, the first alternative is dominated and would be removed. Care must be taken when applying such aggressive screening without considering performance, and should only be applied to specific problems when capability is truly binary with little performance variation.

Finally, one could evaluate portfolios of alternatives in a knapsack-type procedure to ensure no capability gaps exist (a danger when screening based on highest independent capability). This procedure can be implemented if additional constraints exist -- number of potential alternatives, cost of alternatives, etc. -- and can be structured to the specific problem through linear programming techniques.

A modified distance-based screening procedure is used to evaluate the real alternatives in . The subject matter experts have provided the local sub-objective weights (which the analyst

has changed to global weights) and the ideal alternative is known -- that which provides capability in every sub-objective. Alternatives within a certain distance of are selected for further analysis.

With the properties of the ideal known,

(32)

the weighted squared Euclidian method previously presented provides distance information. For all , the normalization factor is now reduced to:

(33)

Thus, the distance between and for is

(34)

and the distance between and for is

(35)

So, the total distance between and is

(36)

and **= {** , where is set by the decision maker to select a certain screened sample size. Increasing increases the number of alternatives in .

Each alternative is examined for dominance. Starting with , is computed, then is compared to ; if contains 's in the same vector positions as another , and that contains a in an additional position, then is dominated and removed from . This is repeated for . Again, caution should be used when implementing this rudimentary screening procedure to ensure helpful alternatives are not eliminated.

Alternatively, dominance can be used to screen by eliminating alternatives that only provide strength in the sub-objectives with lowest global weight. If an alternative only provides functionality to an area of low concern, it will not be among the highest-rated alternatives and will probably not appear in a highly-ranked portfolio. These simple methods of removing alternatives to reduce the model size can help when later running performance-based models with lengthy computing times. As previously stressed, truly eliminating alternatives risks accidentally removing a piece of an ideal portfolio; screening should be performed carefully and depend on the specific problem under evaluation. Screening methods to differentiate "good" and "poor" alternatives can be used to compile a quality portfolio to begin a search algorithm; starting with a solution closer to the ideal will lower search times.

III.E Sufficiency Evaluation

The methodology developed thus far can be used when the process of gathering accurate performance data on a large set of alternatives or alternative combinations is costly or even impossible. It is used to screen alternatives to reduce the size of the alternative set. Next, the analyst must evaluate the remaining possible portfolios, ensuring the portfolio alternatives are sufficient to satisfactorily solve the problem. The analyst should set the distance threshold to reject truly insufficient solutions while allowing sufficiently helpful solutions to remain. In a problem with limited data this may be difficult; there is little guidance in the literature on how to determine which solutions may be sufficient. Previous work leaves this problem element to the decision maker or subject matter experts.

Combining input from the top-level decision maker and bottom-level analysts, a minimum sufficiency level for portfolios of alternatives can be established. This level can be utilized in the secondary performance-based portfolio screening procedure. In many situations, the overall minimum acceptable performance for a solution is generally know, or at least the desired performance. In a problem with significant uncertainty, the difficulty is determining which alternative sets are likely to achieve that performance.

First, the analysts who generate performance measure data establish value functions for their specific area of expertise. These value functions, based on past experience, feature increasing levels of performance on the *x*-axis with the value derived from that level of performance on the *y*-axis, creating a monotonically-increasing function. While a performance-based hierarchy may have a large number of performance measures, each value function is created only once -- a reasonable task given a large number of analysts with specific knowledge of each performance measure.

Next, the top-level decision maker is asked what level of certainty he wishes with this analysis. For example, is the overall decision extremely important and requires high certainty that the screened alternative set will work -- say, 90%? Or perhaps a larger, less-certain set of alternatives would be okay -- a confidence level of 70% may suffice. The selection of a certainty level is the second step.

Third, this certainty level is transferred back down to the analyst level. The confidence percentage the decision maker selects is found on the *y*-axis of each performance measure value function graph, and the value function itself maps this level to the data analysis requirement on the *x*-axis, as shown in Figure 11. Now, the decision maker's single input has been pushed through the hierarchy to determine the data needs to arrive at that level of certainty.

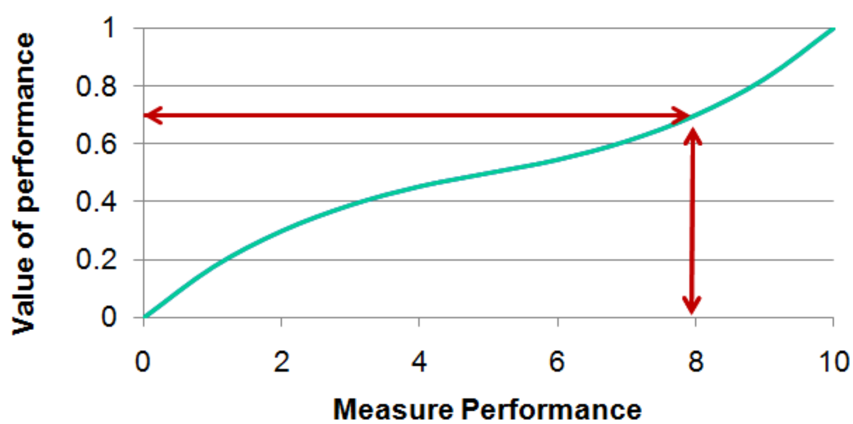


Figure 11: Value function

Finally, the alternatives can be screened on whether they meet the certainty needs of the decision maker. If an alternative (or portfolio) can provide the data at the levels needed by the analysts to meet the decision maker's confidence level, then that alternative is selected for further study. If an alternative (or portfolio) cannot provide the data at the levels needed, then that

alternative is screened out. Post-analysis is performed on the sufficient portfolios examining cost and other considerations. Thus, a screening procedure based on data sufficiency is used to reduce the size of the portfolio set.

III.F Summary

This chapter has clarified the type of problem under consideration: one in which achievement in a series of distinct domains is evaluated through performance in the same set of criteria. Additionally, a large number of alternatives exist leading to a combinatorially-large number of possible portfolios to be evaluated against the hierarchy. A methodology to reduce the number of alternatives was developed with the goal of greatly reducing the number of portfolios considered.

A process of transforming a performance-based hierarchy to a capability-based hierarchy was described. By evaluating individual alternatives on capability, reduction in the size of the alternative set through the elimination of dominated alternatives is achieved. Then, a portfolio sufficiency screening process was developed based on decision maker desires and analyst needs. The final result is a small set of portfolios ready for post-analysis and selection.

IV. Results and Analysis

IV.A Introduction

This chapter applies the developed methodology to a United States Department of Defense Intelligence, Surveillance, and Reconnaissance (ISR) platform portfolio selection problem. The problem features a large number of alternatives leading to a very large number of possible portfolios. The results of various screening procedures are discussed.

IV.B Background

The United States military conducts complex operations with many types of assets. Campaign planners traditionally use combat modeling techniques to determine the most efficient set of weapon assets necessary to achieve victory. It is preferred to use the minimum set of assets that will provide sufficient capability to ensure success.

The recent proliferation of advanced information gathering assets has coincided with the expansion of intelligence requirements stemming from the wars in Iraq and Afghanistan. More ISR assets are available to commanders than ever before. However, the rapid adaptation of these new assets during wartime has led to inefficient use. Study of ideal asset distribution has been largely ignored as military and civilian leadership has demanded immediate deployment in support of soldiers, airmen, and marines.

This has created difficulties in efficiently providing data to the hundreds of units that require information on a timely basis. Some organizations are drowning in data as numerous assets stream terabytes of data to be processed. Meanwhile, other groups are suffering from a lack of the data needed to develop actionable intelligence. ISR assets are not well coordinated across the Department of Defense to ensure an appropriate level of information reaches each

user. Additionally, the patchwork structure of ISR asset usage across services risks that the assets in operation may not be working in an efficient harmony to maximize data obtainment. An analysis of ISR capability is needed to ensure an ideal portfolio of ISR assets is deployed in today's joint environment and developed for future requirements.

Adding to the difficulty of organizing an ideal portfolio is the fundamental ambiguity on the effectiveness of a deployed ISR asset. The clear objectives of typical air assets provide a division between mission initiation and mission success. With strike aircraft, placing a bomb on a specific target provides a clear definition of mission success. With air refueling tankers, loitering in a specific airspace during a specific time while transferring fuel and then returning to base defines a successful mission. For ISR assets, there is no clear measure of success for a specific mission -- the aim is continual data gathering. This data may later be transformed into actionable information to further advance the war effort, but there is not necessarily the immediate recognition of mission success or completeness for an ISR asset during a specific sortie.

Thus, it remains difficult to model ISR tasking appropriately. With traditional strike aircraft, capability and expected effectiveness are known traits -- an F-22 can release a specific weapon that will inflict a known level of damage with a given level of certainty. With ISR assets, the amount of pure data needed to gain a certain amount of actionable intelligence is variable and generally unknown. Thus, unlike traditional force modeling where platform capabilities are summed until the necessary force to meet an objective is created, ISR modeling requires examining the amount, quality, and type of information needed and how best to meet this requirement.

IV.C Application

Hierarchy.

The United States Strategic Command (USSTRATCOM), one of the ten Unified Combatant Commands administered by the United States Department of Defense, is responsible for intelligence, surveillance, and reconnaissance (ISR) operations for the United States military. USSTRATCOM has command authority over the Joint Functional Component Command for Intelligence, Surveillance and Reconnaissance (JFCC-ISR), which coordinates global intelligence collection for worldwide Department of Defense operations and national intelligence requirements (USSTRATCOM, 2010). As the center for planning, execution and assessment of these areas, JFCC-ISR has been tasked to develop an ISR force sizing model. The organization has used multiobjective decision analysis tools to create a hierarchical model to measure the quality of force capabilities. The goal is to develop an ISR portfolio that optimizes value achievement.

The hierarchy consists of seven top level objectives which define domains of ISR necessity, as shown in .

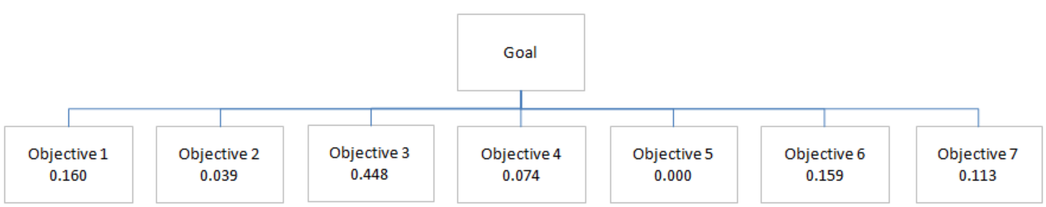


Figure 12: JFCC-ISR hierarchy

Some objectives are more important than others and thus are weighted appropriately; weights are indicated below the objectives. Each objective is defined by an identical set of three

sub-objectives; the relative weight distribution among sub-objectives varies among the objectives. Performance for each of the three sub-objectives is determined by three identical measures; the weight distribution among measures varies among the sub-objectives. The hierarchy for the third objective (of seven) is presented in Figure 13.

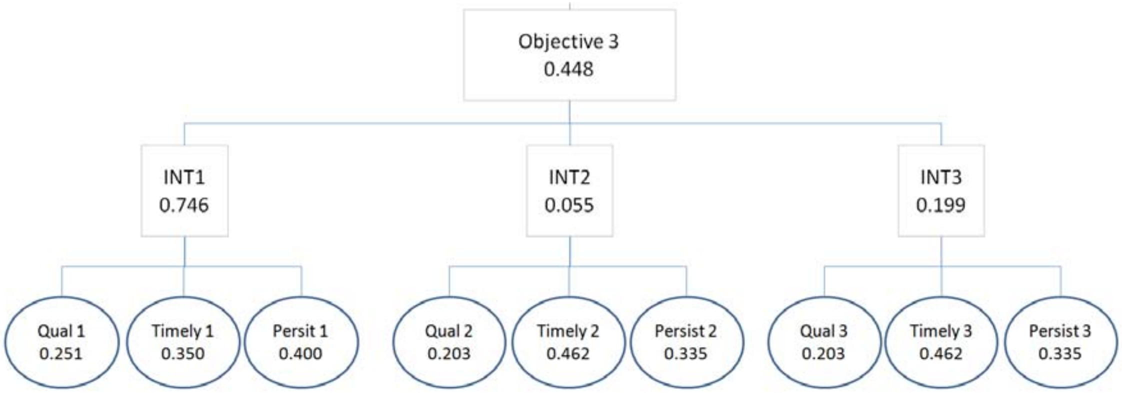


Figure 13: Objective 3 hierarchy

This top level Objective 3, with a weight of 0.448, is evaluated through three sub-objectives which are necessary for its achievement: INT1, INT2, and INT3. These INT sub-objectives represent specific methods of intelligence (INT) collection. The weight for each INT sub-objective, representing the relative importance to the objective achievement, is included. All seven objectives are evaluated on these three sub-objectives, as each objective requires varying levels of the three types of intelligence data to gain understanding in the domain. As certain types of intelligence are more important to some objectives, the weight distribution among the sub-objectives differs for each objective.

Finally, each INT sub-objective is evaluated on the same three measures: quality, timeliness, and persistence. Raw data from an ISR asset can be obtained for these measures, which are rolled up to evaluate sub-objective achievement. The weight for a measure represents its relative importance to achieving the higher-level sub-objective; weight distribution among the three measures differs among sub-objectives and across objectives.

The hierarchy presented here for Objective 3 is repeated for each of the other six objectives. Success in each objective domain is achieved through the same means --achievement in the INT1, INT2, and INT3 sub-objectives, which are evaluated through the same three measures. Thus, the seven objectives lead to 21 sub-objectives and 63 measures. The full hierarchy is shown in Appendix 1.

Alternatives.

The Department of Defense deploys a number of assets to obtain necessary ISR data. Through the development of a clear statement of priorities and the derivative hierarchy, an ideal set of assets can be developed to meet these priorities. This ideal portfolio may consist of any combination of available ISR assets. For some assets, multiple equipment packages can be installed, or the asset may be flown from various locations and follow a number of routes during that flight. These variables lead to a variety of possible platforms for each asset and an enormous number of possible portfolios.

Consider a universe where the Department of Defense owns the following ISR assets: three types of Remotely Piloted Aircraft (RPA), two types of piloted aircraft (AC), and three types of satellites (SAT). These assets are described in Table 4. Two of the RPAs can be flown out of two different bases; thus the number '2' is placed in the 'Bases' column for RPA1 and RPA2 in Table 4. The RPAs and ACs can also be flown on different routes when deployed. Finally, several of the ISR assets can feature multiple equipment packages, as clarified by the Platform Notes. For example, RPA1 and RPA2 each can be loaded with one of two different INT1 packages (INT1a, INT1b) or a package that gathers INT2 and INT3 data (INT2&INT3), for a total of three different packages. AC1 and AC2 have two possible package options: the first is designed for INT2 but obtains some capability in INT3, while the second is designed for

INT3 but obtains some capability in INT2. For initial simplicity, this "some" capability can be considered "half" capability, and will be expanded upon later. All asset/base/route/package options are summarized in Table 4.

Table 4: ISR assets

			Package Options			
SYSTEM	**Bases**	**Routes**	**INT1**	**INT2**	**INT3**	**Platform Notes**
RPA1	2	6	2	1	1	Either INT1 or INT2 and INT3
RPA2	2	6	2	1	1	Either INT1 or INT2 and INT3
RPA3	1	1	1	0	0	INT1 only
AC1	1	2	0	2	2	Better for INT2 but can do INT3
AC2	1	2	0	2	2	Better for INT3 but can do INT2
SAT1	1	1	2	0	0	INT1 only
SAT2	1	1	0	1	0	INT2 only
SAT3	1	1	0	0	1	INT3 only

The number of possible platform combinations for a specific asset can then be calculated. For example, RPA1 can be stationed at two bases, perform six mission routes, and carry one of three packages (INT1a, INT1b, or INT2&INT3). The number of possible combinations is thus . AC1 can be stationed at one base, perform two mission routes, and carry one of two packages (INT2a&INT3a or INT2b&INT3b, with INT2 achieving full capability and INT3 half capability), for a total of four possible combinations. AC2 also has four combinations, but with INT3 achieving full capability and INT2 achieving half capability. Following similar logic, the number of combinations for each asset is presented in Table 5.

Table 5: ISR asset platforms

	Total Platform Combinations
RPA1	36
RPA2	36
RPA3	1
AC1	4
AC2	4
SAT1	2
SAT2	1
SAT3	1

Summing the individual options for inclusion in a portfolio results in 85 possible alternatives. However, an asset can only characterize one option at a time; with only one RPA1, it is not possible to have two RPA1 platforms active at once. To determine the number of portfolios that include all eight assets, the number of platform combinations for each asset are multiplied together:

However, the constraints of a selection problem may mean one must consider combinations of any number of ISR assets. Because the option exists not to select an ISR asset, an additional platform combination must be added for each asset -- a "zero" option of not including an asset in the portfolio. Table 6 reflects this additional option for each asset.

Table 6: ISR asset options

	Total Usage Options
RPA1	37
RPA2	37
RPA3	2
AC1	5
AC2	5
SAT1	3
SAT2	2
SAT3	2

The number of possible portfolios of any size (zero to eight assets) is much larger:

With only eight ISR assets and a handful of variables for each, nearly a million possible portfolios are generated. To evaluate the performance of each of these portfolios against the 63 measures in the full hierarchy requires significant processing time. Currently, JFCC-ISR uses a complex physics-based simulation program to evaluate portfolio performance. Given the high fidelity of the modeling, processing time is approximately three hours for a single portfolio. With this rate of evaluation, a 24-processor computer network would take —

hours, or 11.72 years, to evaluate all possible portfolios.

A slight modification to this problem results in even more extreme evaluation difficulty. The current problem assumes one each of the eight assets. However, instead of one RPA1, what if there exist three RPA1? Similarly, now there are three RPA2, and two each of AC1 and AC2. Certainly, the military possesses multiple copies of most ISR assets, and this example still contains only a few variables for each asset. With only this modification, and leaving all other variables as they were, the new usage options are shown in Table 7.

Table 7: Multiple copies of an asset available

	Total Usage Options
RPA1a	37
RPA1b	37
RPA1c	37
RPA2a	37
RPA2b	37
RPA2c	37
RPA3	2
AC1a	5
AC1b	5
AC2a	5
AC2b	5
SAT1	3
SAT2	2
SAT3	2

This modification results in possible portfolio combinations. With hierarchy performance of each portfolio scored in three hours by a single processor running a simulation program, a 24-processor computer network would take — hours, or years, to evaluate each possible portfolio. Even if the hierarchy performance of a portfolio could be determined in one *second*, the 24-processor computer network would still take 50,849 years to evaluate all possible portfolios. Clearly, even with several factor-of-ten advancements in computing power and speed, solving this problem by evaluating each possible portfolio combination is impractical. Evaluating each portfolio for the full military ISR problem, with dozens of assets with multiple copies and hundreds of platform options, is impossible.

Capability Screening.

Screening the alternatives to eliminate poorly-performing assets or platforms which are unlikely to add value to a good portfolio can greatly reduce the total number of portfolios that

must be evaluated. As previously explored, a small percentage decrease in the number of alternatives in a combinatorial problem can lead to an enormous percentage decrease in the number of combinations. This can allow for the transformation of a problem's full evaluation from impractical to reasonable and allow resources to be better dedicated to refining performance evaluation of the smaller set.

Transforming the ISR performance-based hierarchy to a capability-based hierarchy is the first step in this screening process. This transformation will determine which sub-objectives and associated measures of the seven top-level objectives are most important through the assignment of global weights. Then, the alternatives can be assessed on their capability in each area, to determine which assets contribute little capability and/or are dominated.

From the local weights provided in the original hierarchy, the global weights for each objective, sub-objective, and measure can be determined, as shown in Table 8.

Table 8: Objective, sub-objective, and measure weights

			Local Weight	Global Weight				Local Weight	Global Weight
Objective 1			0.168	0.168	**Objective 4**			0.074	0.074
	INT1.1		1.000	0.168		INT1.4		0.746	0.055
		Qual 1.1	0.397	0.067			Qual 1.4	0.251	0.014
		Timely 1.1	0.178	0.030			Timely 1.4	0.350	0.019
		Persist 1.1	0.425	0.071			Persist 1.4	0.400	0.022
	INT2.1		0.000	0.000		INT2.4		0.055	0.004
		Qual 2.1	0.000	0.000			Qual 2.4	0.203	0.001
		Timely 2.1	0.000	0.000			Timely 2.4	0.462	0.002
		Persist 2.1	0.000	0.000			Persist 2.4	0.335	0.001
	INT3.1		0.000	0.000		INT3.4		0.199	0.015
		Qual 3.1	0.000	0.000			Qual 3.4	0.203	0.003
		Timely 3.1	0.000	0.000			Timely 3.4	0.462	0.007
		Persist 3.1	0.000	0.000			Persist 3.4	0.335	0.005
Objective 2			0.039	0.039	**Objective 5**			0.000	0.000
	INT1.2		1.000	0.039		INT1.5		0.000	0.000
		Qual 1.2	0.251	0.010			Qual 1.5	0.000	0.000
		Timely 1.2	0.350	0.013			Timely 1.5	0.000	0.000
		Persist 1.2	0.400	0.015			Persist 1.5	0.000	0.000
	INT2.2		0.000	0.000		INT2.5		0.000	0.000
		Qual 2.2	0.000	0.000			Qual 2.5	0.000	0.000
		Timely 2.2	0.000	0.000			Timely 2.5	0.000	0.000
		Persist 2.2	0.000	0.000			Persist 2.5	0.000	0.000
	INT3.2		0.000	0.000		INT3.5		0.000	0.000
		Qual 3.2	0.000	0.000			Qual 3.5	0.000	0.000
		Timely 3.2	0.000	0.000			Timely 3.5	0.000	0.000
		Persist 3.2	0.000	0.000			Persist 3.5	0.000	0.000
Objective 3			0.448	0.448	**Objective 6**			0.159	0.159
	INT1.3		0.746	0.334		INT1.6		0.000	0.000
		Qual 1.3	0.251	0.084			Qual 1.6	0.000	0.000
		Timely 1.3	0.350	0.117			Timely 1.6	0.000	0.000
		Persist 1.3	0.400	0.134			Persist 1.6	0.000	0.000
	INT2.3		0.055	0.024		INT2.6		0.458	0.073
		Qual 2.3	0.203	0.005			Qual 2.6	0.203	0.015
		Timely 2.3	0.462	0.011			Timely 2.6	0.462	0.034
		Persist 2.3	0.335	0.008			Persist 2.6	0.335	0.024
	INT3.3		0.199	0.089		INT3.6		0.542	0.086
		Qual 3.3	0.203	0.018			Qual 3.6	0.203	0.017
		Timely 3.3	0.462	0.041			Timely 3.6	0.462	0.040
		Persist 3.3	0.335	0.030			Persist 3.6	0.335	0.029
					Objective 7			0.113	0.113
						INT1.7		0.146	0.017
							Qual 1.7	0.251	0.004
							Timely 1.7	0.350	0.006
							Persist 1.7	0.400	0.007
						INT2.7		0.427	0.048
							Qual 2.7	0.203	0.010
							Timely 2.7	0.462	0.022
							Persist 2.7	0.335	0.016
						INT3.7		0.427	0.048
							Qual 3.7	0.203	0.010
							Timely 3.7	0.462	0.022
							Persist 3.7	0.335	0.016

Several of the sub-objective and measure global weights are zero; this is an artifact of the alternatives available when the original JFCC-ISR hierarchy was created, but will not negatively affect the validity of this analysis. By summing the appropriate global weights, the importance of each sub-objective and measure can be calculated, as shown in Table 9.

Table 9: Sub-objective and measure weights across all objectives

	INT1	INT2	INT3	
Quality	0.178	0.030	0.048	**0.257**
Timeliness	0.185	0.069	0.110	**0.365**
Persistence	0.249	0.050	0.080	**0.379**
	0.612	**0.150**	**0.239**	

INT1 is the most important of the three sub-objectives, providing 61.2% of the overall value in all objectives, while INT2 is least important at 15.0% of the value. The measures are more evenly distributed, with Persistence (37.9%) and Timeliness (36.5%) most important and Quality (25.7%) the least.

A capability-based hierarchy can be created with these global weights, shown in Figure 14.

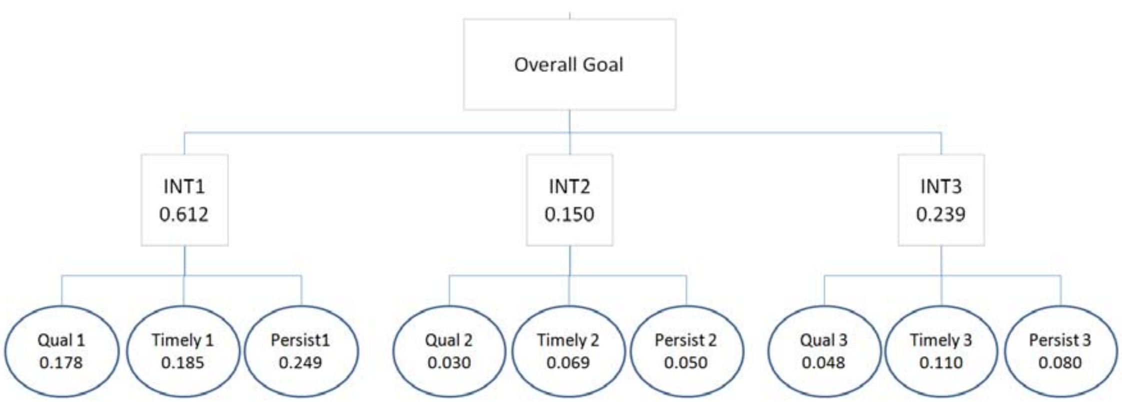


Figure 14: Condensed hierarchy with global weights

Or, simpler hierarchies of only sub-objectives (Figure 15) or only measures (Figure 16) can be created.

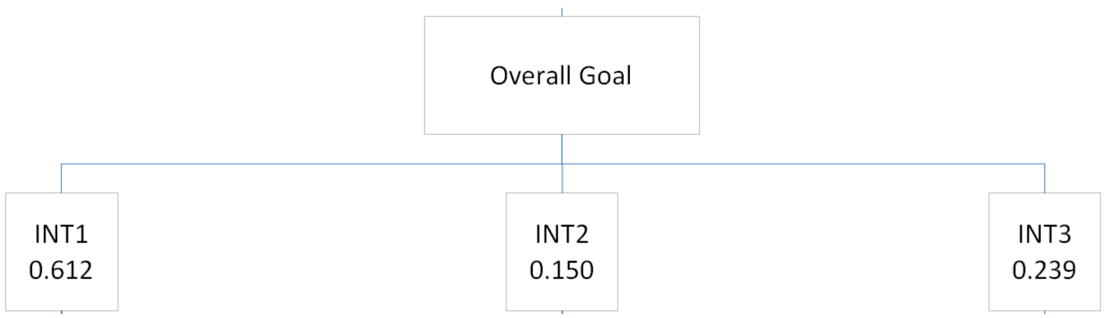


Figure 15: Condensed sub-objective hierarchy

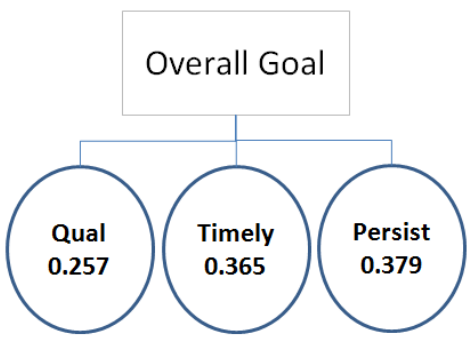


Figure 16: Condensed measure hierarchy

These hierarchies, reduced to the sub-objective and measure level, can now be used as capability-based hierarchies. The sub-objective capability-based hierarchy allows for evaluation of the alternatives based on their intended INT capability. An alternative's score is calculated by summing the weights for each sub-objective an alternative is designed to achieve.

For example, RPA1 version *3* carries a package that gathers INT2 and INT3 data, thus providing capability in these two sub-objective areas. The weights of these two areas, 0.150 and 0.239, are summed to give a capability score for this alternative of 0.389. Table 10 displays capability-based evaluations of each alternative for the initial case of single copies of each ISR asset. For each alternative, the grey shading represents in which sub-objective that alternative is designed to provide capability; the number in each cell specifies the base/route/platform option. For AC1 and AC2, where each platform option is designed to accomplish one sub-objective well and one moderately, a "half" factor of 0.5 was used to represent this moderate capability. The table is sorted from highest to lowest value score.

Table 10: Capability value scores

		Platform Variables					
System	Version	Base	Route	INT1	INT2	INT3	Score
RPA1	*1*	1	1	1	0	0	0.612
RPA1	*2*	1	1	2	0	0	0.612
RPA1	*4*	1	2	1	0	0	0.612
RPA1	*5*	1	2	2	0	0	0.612
RPA1	*7*	1	3	1	0	0	0.612
RPA1	*8*	1	3	2	0	0	0.612
RPA1	*10*	1	4	1	0	0	0.612
RPA1	*11*	1	4	2	0	0	0.612
RPA1	*13*	1	5	1	0	0	0.612
RPA1	*14*	1	5	2	0	0	0.612
RPA1	*16*	1	6	1	0	0	0.612
RPA1	*17*	1	6	2	0	0	0.612
RPA1	*19*	2	1	1	0	0	0.612
RPA1	*20*	2	1	2	0	0	0.612
RPA1	*22*	2	2	1	0	0	0.612
RPA1	*23*	2	2	2	0	0	0.612
RPA1	*25*	2	3	1	0	0	0.612
RPA1	*26*	2	3	2	0	0	0.612
RPA1	*28*	2	4	1	0	0	0.612
RPA1	*29*	2	4	2	0	0	0.612
RPA1	*31*	2	5	1	0	0	0.612
RPA1	*32*	2	5	2	0	0	0.612
RPA1	*34*	2	6	1	0	0	0.612
RPA1	*35*	2	6	2	0	0	0.612
RPA2	*1*	1	1	1	0	0	0.612
RPA2	*2*	1	1	2	0	0	0.612
RPA2	*4*	1	2	1	0	0	0.612
RPA2	*5*	1	2	2	0	0	0.612
RPA2	*7*	1	3	1	0	0	0.612
RPA2	*8*	1	3	2	0	0	0.612
RPA2	*10*	1	4	1	0	0	0.612
RPA2	*11*	1	4	2	0	0	0.612
RPA2	*13*	1	5	1	0	0	0.612
RPA2	*14*	1	5	2	0	0	0.612
RPA2	*16*	1	6	1	0	0	0.612
RPA2	*17*	1	6	2	0	0	0.612
RPA2	*19*	2	1	1	0	0	0.612
RPA2	*20*	2	1	2	0	0	0.612
RPA2	*22*	2	2	1	0	0	0.612
RPA2	*23*	2	2	2	0	0	0.612
RPA2	*25*	2	3	1	0	0	0.612
RPA2	*26*	2	3	2	0	0	0.612
RPA2	*28*	2	4	1	0	0	0.612
RPA2	*29*	2	4	2	0	0	0.612
RPA2	*31*	2	5	1	0	0	0.612
RPA2	*32*	2	5	2	0	0	0.612
RPA2	*34*	2	6	1	0	0	0.612
RPA2	*35*	2	6	2	0	0	0.612
RPA3	*1*	1	1	1	0	0	0.612
SAT1	*1*	1	1	1	0	0	0.612
SAT1	*2*	1	1	2	0	0	0.612
RPA1	*3*	1	1	0	1	1	0.389
RPA1	*6*	1	2	0	1	1	0.389
RPA1	*9*	1	3	0	1	1	0.389
RPA1	*12*	1	4	0	1	1	0.389
RPA1	*15*	1	5	0	1	1	0.389
RPA1	*18*	1	6	0	1	1	0.389
RPA1	*21*	2	1	0	1	1	0.389
RPA1	*24*	2	2	0	1	1	0.389
RPA1	*27*	2	3	0	1	1	0.389
RPA1	*30*	2	4	0	1	1	0.389
RPA1	*33*	2	5	0	1	1	0.389
RPA1	*36*	2	6	0	1	1	0.389
RPA2	*3*	1	1	0	1	1	0.389
RPA2	*6*	1	2	0	1	1	0.389
RPA2	*9*	1	3	0	1	1	0.389
RPA2	*12*	1	4	0	1	1	0.389
RPA2	*15*	1	5	0	1	1	0.389
RPA2	*18*	1	6	0	1	1	0.389
RPA2	*21*	2	1	0	1	1	0.389
RPA2	*24*	2	2	0	1	1	0.389
RPA2	*27*	2	3	0	1	1	0.389
RPA2	*30*	2	4	0	1	1	0.389
RPA2	*33*	2	5	0	1	1	0.389
RPA2	*36*	2	6	0	1	1	0.389
AC2	*1*	1	1	0	0.5	1	0.314
AC2	*2*	1	1	0	0.5	1	0.314
AC2	*3*	1	2	0	0.5	1	0.314
AC2	*4*	1	2	0	0.5	1	0.314
AC1	*1*	1	1	0	1	0.5	0.270
AC1	*2*	1	1	0	1	0.5	0.270
AC1	*3*	1	2	0	1	0.5	0.270
AC1	*4*	1	2	0	1	0.5	0.270
SAT3	*1*	1	1	0	0	1	0.239
SAT2	*1*	1	1	0	1	0	0.150
RPA1	*0*	0	0	0	0	0	0.000
RPA2	*0*	0	0	0	0	0	0.000
RPA3	*0*	0	0	0	0	0	0.000
AC1	*0*	0	0	0	0	0	0.000
AC2	*0*	0	0	0	0	0	0.000
SAT1	*0*	0	0	0	0	0	0.000
SAT2	*0*	0	0	0	0	0	0.000
SAT3	*0*	0	0	0	0	0	0.000

The assets that provide INT1 capability are most valued, followed by those that provide INT2 and INT3 in various combinations. Finally, the assets that provide only INT2 or only

INT3 round out the bottom of the alternatives that provide value. Of course, the "zero option" of not using an ISR asset results in zero value added.

Now that alternative capability scores have been calculated, initial screening can begin. The rough screening process described next creates a structure that will be built on further. Depending on the constraints of the portfolio selection problem, some alternatives may be eliminated based on pure dominance. This elimination of alternatives based solely on capability scores is an aggressive screening method, and should be used with caution. Problems with alternatives of clearly binary capability, without significant shades of performance, may be appropriate for this method. More refined screening methods will be described later.

If one is allowed to select any number of assets, naturally one would choose all eight assets for maximum capability. However, if a constraint exists that states only a subset of the total number of assets may be selected, then an asset that is dominated by another asset in a certain set of sub-objectives can be removed. Suppose one wishes to maximize total value but also to achieve value in all three INT areas, and only two of the eight assets can be selected. An asset that provides less capability than another asset in a specific sub-objective set can be eliminated through total dominance. In this case, all versions of AC2 (0.314) and AC1 (0.270), as well as SAT3 (0.239) and SAT2 (0.150), are dominated in INT2 and INT3 by the "INT2 & INT3" versions of RPA1 (0.389) and RPA2 (0.389). Thus, one would pick an INT1 package among RPA1, RPA2, RPA3, and SAT1, and an "INT2 & INT3" package from RPA1 or RPA2. Note that RPA1 or RPA2 can only be selected to fulfill one of those sub-objective sets, as in this example there is only one copy available of each asset. If one chooses RPA 1 for INT1, one could not choose it also for "INT2 & INT3."

This eliminates 10 alternatives from the set, reducing the number of alternatives for a potential portfolio from 93 to 83, as shown in Table 11.

Table 11: Alternative reduction

System	Total Platforms	After Screening
RPA1	37	37
RPA2	37	37
RPA3	2	2
AC1	5	1
AC2	5	1
SAT1	3	3
SAT2	2	1
SAT3	2	1

However, the time to solve is greatly improved, as seen in Table 12.

Table 12: Combination reduction

	Original	After Screening	% Reduction
Total Alternatives	93	83	10.75%
Total Combinations	821400	8214	99.00%
Time to solve (days)	4278.1	42.8	99.00%

Reducing the number of alternatives by 10.75% through removing dominated assets reduces the total number of portfolios, and thus the time to solve, by 99%. Table 12 shows time to solve with a 24-processor network when each portfolio is processed in three hours. This processing time definition is arbitrary; the percent reduction in total combinations (and thus reduction in time to solve, no matter the unit) is 99%, an incredible savings. As the type of constraint changes, such as number of allowable assets, more or fewer assets can be eliminated, adjusting the percent reduction in time to solve.

This basic screening can be used to account for other constraints. If one type of aircraft must be chosen, it would be advantageous to choose AC2 (0.314) over AC1 (0.270), as AC2 is stronger in INT3, which is weighted heavier (and thus contributes more value to the full hierarchy) than AC1's INT2 strength. If two of the three satellites must be chosen, the best combination is SAT1 (0.612) and SAT3 (0.239). These types of alternative-selection problems can be solved using standard mixed integer programming techniques with simple constraints.

Other times, inherent properties are known about two similar ISR assets. For example, consider RPA1 and RPA2. Each has identical basing, route, and platform options. It may be known that RPA1 is a newer, updated version of RPA2. Thus, it can be assumed that RPA1, though it is designed to have the same capability set as RPA2, actually performs at a better level operationally. Exact performance data is not needed; the knowledge that as RPA1 was created to improve upon RPA2 allows for the assumption that RPA1 performs better than RPA2. Whenever an RPA1 platform provides the identical sub-objective capability set as RPA2, the RPA2 platform can be eliminated as its performance is assumed to be dominated. (In a more rigorous analysis it might be necessary to consider other factors such as cost of operation, which may dissuade elimination.) In the situation under examination, RPA1 and RPA2 both provide three possible platform configurations (two versions of INT1 plus one version of "INT2 & INT3"). If a constraint exists that only one RPA asset may be selected, because it is assumed RPA1 provides better inherent capability than RPA2, RPA2 can be eliminated from the alternative set. This results in the post-screening alternative list in Table 13.

Table 13: Alternative reduction

System	Total Platforms	After Screening
RPA1	37	37
RPA2	37	1
RPA3	2	2
AC1	5	5
AC2	5	5
SAT1	3	3
SAT2	2	2
SAT3	2	2

This type of logical screening, possible during capability-based examination, can greatly reduce the number of potential portfolio combinations as shown in Table 14.

Table 14: Combination reduction

	Original	After Screening	% Reduction
Total Alternatives	93	57	38.71%
Total Combinations	821400	22200	97.30%
Time to solve (days)	4278.1	115.6	97.30%

Eliminating RPA2 from consideration reduces the total number of alternatives by 38.71%, and reduces the number of portfolios (and thus time to solve) by 97.30%.

Note that in this case, 38.71% of alternatives eliminated produced a *lower* percentage reduction in total combinations (97.30%) than in the previous case when 10.75% of alternatives were eliminated (99.00%). When eliminating alternatives from one asset, the percent reduction in alternatives can be much higher (38.71% vs. 10.75%), but the percent reduction in total combinations may be lower (97.30% vs. 99.00%). This is a function of the multiplicative nature of calculating total combinations. The first case removed a multiplicative factor of 100 through the removal of 10 alternatives: AC1 platforms from five to one (removal of multiplicative factor

of 5), AC2 from five to one (5), SAT2 from two to one (2), and SAT3 from two to one (2), and The second case removed a multiplicative factor of 37 through the elimination of 36 alternatives. Thus, it is generally better to screen and eliminate platforms from multiple assets than only to remove a large number of platforms from one asset. The number of alternatives eliminated is not a perfect indicator of percentage decrease in the number of combinations.

Advanced Screening.

The binary capability-based screening process previously described is useful for eliminating totally dominated alternatives. However, many times an alternative will not be completely dominated by another alternative; organizational efficiencies tend to eliminate redundant assets. It may be useful to perform a more detailed procedure that is fundamentally capability-based but adds a slight layer of estimated alternative performance for each capability. This process requires more resources initially, but can be accomplished in an entirely reasonable amount of time and greatly reduces the time and cost necessary for later detailed portfolio performance-based analysis.

This new process uses the rolled-up hierarchy that consolidated sub-objectives and measures for each objective, as shown in Figure 14. This level of granularity may be necessary if the measures of Quality, Timeliness, and Persistence cannot be generalized across all sub-objectives. An alternative cannot be given a single score to represent "quality," because quality in the INT1 domain may be quite different than quality in the INT3 domain. Similarly, beyond the most basic capability-based analysis, it is not good practice to give an alternative a binary score for capability in a sub-objective. For example, an asset may be designed to provide capability in INT3, but achieves this through extreme strength in Quality 3. Because Quality 3 is

a low-weighted measure for INT3, that asset is really only achieving 1/6th of the possible INT3 value.

A better primary analysis can yield much better information on alternative value, and thus which alternatives may comprise better portfolios. Establishing quality alternatives through primary analysis allows for the confident elimination of poor alternatives, thus reducing the number of portfolios. Then, better starting points for a response surface methodology algorithmic search in conjunction with the detailed physics-based computer portfolio simulations can be created.

To begin, each of the nine measures is assigned a value function that maps an alternative's estimated capability level in a measure to the value of that capability level. These value functions are operational for every alternative, so they are allowed to be broad, even categorical if necessary, to account for the wide range of capabilities and levels of performance ISR assets provide. Because these value functions operate on the condensed hierarchy, they are defined by the capability range of the alternative set itself, not for any specific objective domain.

Once the nine value functions are created, the subject matter expert for each asset scores each of his asset's platform alternatives in each measure. Each asset alternative may achieve different value in a measure based on its platform options (i.e., base, route, ISR package). The asset subject matter expert estimates each platform's capability level, which is then mapped to a value through the value functions. This task should not present significant difficulty to a party familiar with an asset's capabilities under different conditions. Each asset is scored by a different subject matter expert, so the total work is spread among a large number of people. This may prove the lengthiest part of the process in terms of man-hours, but the work can be done concurrently and adds tremendous value to the fidelity of this screening methodology.

Expanding on the ISR example explored previously, let the measure value functions be defined categorically as shown in Table 15.

Table 15: Categorical value functions

		Value		
INT1	**Definiton**	**Low**	**Medium**	**High**
Quality 1	resolution	0.10	0.60	0.95
Timeliness 1	transmission time	0.30	0.60	0.90
Persistence 1	collections per day	0.40	0.60	0.80
INT2				
Quality 2	minimum signal/noise ratio	0.40	0.50	0.75
Timeliness 2	transmission time	0.60	0.70	0.80
Persistence 2	time in operation	0.55	0.75	0.95
INT3				
Quality 3	minimum signal/noise ratio	0.20	0.60	0.90
Timeliness 3	transmission time	0.20	0.70	0.95
Persistence 3	time in operation	0.30	0.80	0.95

The definitions for INT2 and INT3 are identical because these methods of intelligence collection are similar in nature. The value functions differ because the distribution of alternative capability level in a measure is different between the two sub-objectives, as is the value to a sub-objective of certain levels of capability.

An ISR alternative that provides low resolution for INT1 achieves a value of 0.10 for the INT1 Quality measure. (Actual low, medium, and high capability level definitions for each measure are available but classified and not included here.) Multiplying this value by the global weight of the INT1 Quality measure (0.178) gives 0.0178 as the weighted measure value achieved. This process is repeated for each of the nine measures, and the sum of the weighted measure values provides the score for that alternative.

The subject matter experts evaluate the set of nine measures for each of an asset's platforms. While it seems a large number of evaluations must occur, with categorical value functions, many platforms are likely to have identical value in certain measures. Additionally, many of the measures will simply be assigned a value of zero (not low) if a platform provides no capability in that sub-objective, thus simplifying the process. It is assumed that no platform is perfect and thus there is no option for a value score of one. If an "ideal" platform can be defined, it can be included as a category with value one.

The assets under consideration in this example vary in sub-objective performance as a function of base, route, and package. Persistence signifies the quantity of data the ISR asset provides, which is commonly a function of the amount of time spent collecting data. Persistence can be affected by the route a asset takes, as some flight paths may provide a longer duration of target coverage. The RPAs score high in persistence on routes 1 and 2, which are direct paths to the target area. The RPAs score low in persistence for routes 5 and 6, which require a longer travel path until the RPA nears the target; only a short loiter time far from the target is possible before the RPA must return for fuel. RPA routes 3 and 4 fall between these extremes. The ACs can follow two possible routes: route 1 allows for direct travel and high persistence, while route 2 requires a longer path and thus only medium persistence before the aircraft must return to base. The three SATs are always in geosynchronous orbit and are capable of constant surveillance; thus, high persistence.

Timeliness refers to the speed at which an ISR asset can provide raw data to the analysis center for transformation into useable information, and thus is a function of the asset. RPA1 possesses high timeliness due to upgraded software and hardware assets that allow for powerful compression and fast transmission. RPA2 and RPA3, as well as AC1 and AC2, utilize older

technology that cannot transmit as efficiently, and thus exhibit medium timeliness. Naturally, the ever-present SATs also possess high timeliness.

Quality is a function of asset, route, and the specific ISR package installed on the asset. The newer RPA1 has better technology, while RPA2 and RPA3 have older packages installed. Routes 2 and 4 bring an RPA closer to the target area, leading to higher quality data, but there is a risk of interference from the enemy. Routes 1 and 3 keep an RPA safer by following a path farther from the target area, but thus lead to lower quality data. So, RPA1 following route 2 or 4 achieves high quality, while route 1 or 3 leads to medium quality. For RPA2, route 2 or 4 achieves medium quality, while route 1 or 3 leads to low quality. Routes 5 and 6 are far from the target area and thus have low quality for all RPAs. AC1 can carry a high quality INT2 package and medium quality INT3 package, while AC2 can carry medium quality INT2 and high quality INT3; their packages are such that route does not change performance enough to move value function category. The SATs all offer high quality capabilities.

With the values achieved in each measure established, an alternative can be scored by multiplying the value for a measure by the global weight of that measure. For example, scoring for RPA1 version *3* is shown in Table 16.

Table 16: Scoring for an alternative

							INT1			INT2			INT3			
		Option					Quality 1	Timeliness 1	Persistence 1	Quality 2	Timeliness 2	Persistence 2	Quality 3	Timeliness 3	Persistence 3	
System	Version	Base	Route	INT1	INT2	INT3	0.178	0.185	0.249	0.030	0.069	0.050	0.048	0.110	0.080	Total Score
RPA1	*3*	1	1	0	1	1	0	0	0	0.50	0.80	0.95	0.60	0.95	0.95	0.3270

This platform achieves value of 0.50 for Quality 2, 0.80 for Timeliness 2, and 0.95 for Persistence 2, plus 0.60 for Quality 3, 0.95 for Timeliness 3, and 0.95 for Persistence 3.

Multiplying each value by its respective weight (found in Table 16 row 3 under the measure name) and summing results in a total score of 0.3270.

Table 17 shows the list of scored alternatives sorted by total value achieved.

Table 17: Scoring for all alternatives

							INT1			INT2			INT3			
		Option					Quality 1	Timeliness 1	Persistence 1	Quality 2	Timeliness 2	Persistence 2	Quality 3	Timeliness 3	Persistence 3	
System	Version	Base	Route	INT1	INT2	INT3	0.178	0.185	0.249	0.030	0.069	0.050	0.048	0.110	0.080	Total Score
RPA1	*4*	1	2	1	0	0	0.95	0.90	0.80	0	0	0	0	0	0	0.5348
RPA1	*5*	1	2	2	0	0	0.95	0.90	0.80	0	0	0	0	0	0	0.5348
RPA1	*22*	2	2	1	0	0	0.95	0.90	0.80	0	0	0	0	0	0	0.5348
RPA1	*23*	2	2	2	0	0	0.95	0.90	0.80	0	0	0	0	0	0	0.5348
SAT1	*1*	1	1	1	0	0	0.95	0.90	0.80	0	0	0	0	0	0	0.5348
SAT1	*2*	1	1	2	0	0	0.95	0.90	0.80	0	0	0	0	0	0	0.5348
RPA1	*10*	1	4	1	0	0	0.95	0.90	0.60	0	0	0	0	0	0	0.4850
RPA1	*11*	1	4	2	0	0	0.95	0.90	0.60	0	0	0	0	0	0	0.4850
RPA1	*28*	2	4	1	0	0	0.95	0.90	0.60	0	0	0	0	0	0	0.4850
RPA1	*29*	2	4	2	0	0	0.95	0.90	0.60	0	0	0	0	0	0	0.4850
RPA2	*4*	1	2	1	0	0	0.95	0.60	0.80	0	0	0	0	0	0	0.4793
RPA2	*5*	1	2	2	0	0	0.95	0.60	0.80	0	0	0	0	0	0	0.4793
RPA2	*22*	2	2	1	0	0	0.95	0.60	0.80	0	0	0	0	0	0	0.4793
RPA2	*23*	2	2	2	0	0	0.95	0.60	0.80	0	0	0	0	0	0	0.4793
RPA1	*1*	1	1	1	0	0	0.60	0.90	0.80	0	0	0	0	0	0	0.4725
RPA1	*2*	1	1	2	0	0	0.60	0.90	0.80	0	0	0	0	0	0	0.4725
RPA1	*19*	2	1	1	0	0	0.60	0.90	0.80	0	0	0	0	0	0	0.4725
RPA1	*20*	2	1	2	0	0	0.60	0.90	0.80	0	0	0	0	0	0	0.4725
RPA2	*10*	1	4	1	0	0	0.95	0.60	0.60	0	0	0	0	0	0	0.4295
RPA2	*11*	1	4	2	0	0	0.95	0.60	0.60	0	0	0	0	0	0	0.4295
RPA2	*28*	2	4	1	0	0	0.95	0.60	0.60	0	0	0	0	0	0	0.4295
RPA2	*29*	2	4	2	0	0	0.95	0.60	0.60	0	0	0	0	0	0	0.4295
RPA1	*7*	1	3	1	0	0	0.60	0.90	0.60	0	0	0	0	0	0	0.4227
RPA1	*8*	1	3	2	0	0	0.60	0.90	0.60	0	0	0	0	0	0	0.4227
RPA1	*25*	2	3	1	0	0	0.60	0.90	0.60	0	0	0	0	0	0	0.4227
RPA1	*26*	2	3	2	0	0	0.60	0.90	0.60	0	0	0	0	0	0	0.4227
RPA2	*1*	1	1	1	0	0	0.60	0.60	0.80	0	0	0	0	0	0	0.4170
RPA2	*2*	1	1	2	0	0	0.60	0.60	0.80	0	0	0	0	0	0	0.4170
RPA2	*19*	2	1	1	0	0	0.60	0.60	0.80	0	0	0	0	0	0	0.4170
RPA2	*20*	2	1	2	0	0	0.60	0.60	0.80	0	0	0	0	0	0	0.4170
RPA3	*1*	1	1	1	0	0	0.60	0.60	0.80	0	0	0	0	0	0	0.4170
RPA2	*7*	1	3	1	0	0	0.60	0.60	0.60	0	0	0	0	0	0	0.3672
RPA2	*8*	1	3	2	0	0	0.60	0.60	0.60	0	0	0	0	0	0	0.3672
RPA2	*25*	2	3	1	0	0	0.60	0.60	0.60	0	0	0	0	0	0	0.3672
RPA2	*26*	2	3	2	0	0	0.60	0.60	0.60	0	0	0	0	0	0	0.3672
RPA1	*6*	1	2	0	1	1	0	0	0	0.75	0.80	0.95	0.90	0.95	0.95	0.3489
RPA1	*24*	2	2	0	1	1	0	0	0	0.75	0.80	0.95	0.90	0.95	0.95	0.3489
RPA1	*3*	1	1	0	1	1	0	0	0	0.50	0.80	0.95	0.60	0.95	0.95	0.3270
RPA1	*21*	2	1	0	1	1	0	0	0	0.50	0.80	0.95	0.60	0.95	0.95	0.3270
RPA1	*12*	1	4	0	1	1	0	0	0	0.75	0.80	0.75	0.90	0.95	0.80	0.3269
RPA1	*30*	2	4	0	1	1	0	0	0	0.75	0.80	0.75	0.90	0.95	0.80	0.3269
RPA2	*6*	1	2	0	1	1	0	0	0	0.75	0.70	0.95	0.90	0.70	0.95	0.3145
RPA2	*24*	2	2	0	1	1	0	0	0	0.75	0.70	0.95	0.90	0.70	0.95	0.3145
RPA1	*9*	1	3	0	1	1	0	0	0	0.50	0.80	0.75	0.60	0.95	0.80	0.3050
RPA1	*27*	2	3	0	1	1	0	0	0	0.50	0.80	0.75	0.60	0.95	0.80	0.3050
AC2	*1*	1	1	0	1	1	0	0	0	0.50	0.70	0.95	0.90	0.70	0.80	0.2950
AC2	*2*	1	1	0	2	2	0	0	0	0.50	0.70	0.95	0.90	0.70	0.80	0.2950
RPA2	*3*	1	1	0	1	1	0	0	0	0.50	0.70	0.95	0.60	0.70	0.95	0.2926
RPA2	*21*	2	1	0	1	1	0	0	0	0.50	0.70	0.95	0.60	0.70	0.95	0.2926
RPA2	*12*	1	4	0	1	1	0	0	0	0.75	0.70	0.75	0.90	0.70	0.80	0.2925
RPA2	*30*	2	4	0	1	1	0	0	0	0.75	0.70	0.75	0.90	0.70	0.80	0.2925
AC1	*1*	1	1	0	1	1	0	0	0	0.75	0.70	0.95	0.60	0.70	0.80	0.2881
AC1	*2*	1	1	0	2	2	0	0	0	0.75	0.70	0.95	0.60	0.70	0.80	0.2881
AC2	*3*	1	2	0	1	1	0	0	0	0.50	0.70	0.75	0.90	0.70	0.80	0.2850
AC2	*4*	1	2	0	2	2	0	0	0	0.50	0.70	0.75	0.90	0.70	0.80	0.2850
RPA1	*13*	1	5	1	0	0	0.10	0.90	0.40	0	0	0	0	0	0	0.2839
RPA1	*14*	1	5	2	0	0	0.10	0.90	0.40	0	0	0	0	0	0	0.2839
RPA1	*16*	1	6	1	0	0	0.10	0.90	0.40	0	0	0	0	0	0	0.2839
RPA1	*17*	1	6	2	0	0	0.10	0.90	0.40	0	0	0	0	0	0	0.2839
RPA1	*31*	2	5	1	0	0	0.10	0.90	0.40	0	0	0	0	0	0	0.2839
RPA1	*32*	2	5	2	0	0	0.10	0.90	0.40	0	0	0	0	0	0	0.2839
RPA1	*34*	2	6	1	0	0	0.10	0.90	0.40	0	0	0	0	0	0	0.2839
RPA1	*35*	2	6	2	0	0	0.10	0.90	0.40	0	0	0	0	0	0	0.2839

AC1	*3*	1	2	0	1	1	0	0	0	0.75	0.70	0.75	0.60	0.70	0.80	0.2781
AC1	*4*	1	2	0	2	2	0	0	0	0.75	0.70	0.75	0.60	0.70	0.80	0.2781
RPA2	*9*	1	3	0	1	1	0	0	0	0.50	0.70	0.75	0.60	0.70	0.80	0.2706
RPA2	*27*	2	3	0	1	1	0	0	0	0.50	0.70	0.75	0.60	0.70	0.80	0.2706
RPA1	*15*	1	5	0	1	1	0	0	0	0.40	0.80	0.55	0.20	0.95	0.30	0.2328
RPA1	*18*	1	6	0	1	1	0	0	0	0.40	0.80	0.55	0.20	0.95	0.30	0.2328
RPA1	*33*	2	5	0	1	1	0	0	0	0.40	0.80	0.55	0.20	0.95	0.30	0.2328
RPA1	*36*	2	6	0	1	1	0	0	0	0.40	0.80	0.55	0.20	0.95	0.30	0.2328
RPA2	*13*	1	5	1	0	0	0.10	0.60	0.40	0	0	0	0	0	0	0.2284
RPA2	*14*	1	5	2	0	0	0.10	0.60	0.40	0	0	0	0	0	0	0.2284
RPA2	*16*	1	6	1	0	0	0.10	0.60	0.40	0	0	0	0	0	0	0.2284
RPA2	*17*	1	6	2	0	0	0.10	0.60	0.40	0	0	0	0	0	0	0.2284
RPA2	*31*	2	5	1	0	0	0.10	0.60	0.40	0	0	0	0	0	0	0.2284
RPA2	*32*	2	5	2	0	0	0.10	0.60	0.40	0	0	0	0	0	0	0.2284
RPA2	*34*	2	6	1	0	0	0.10	0.60	0.40	0	0	0	0	0	0	0.2284
RPA2	*35*	2	6	2	0	0	0.10	0.60	0.40	0	0	0	0	0	0	0.2284
SAT3	*1*	1	1	0	0	1	0	0	0	0	0	0	0.90	0.95	0.95	0.2237
RPA2	*15*	1	5	0	1	1	0	0	0	0.40	0.70	0.55	0.20	0.70	0.30	0.1984
RPA2	*18*	1	6	0	1	1	0	0	0	0.40	0.70	0.55	0.20	0.70	0.30	0.1984
RPA2	*33*	2	5	0	1	1	0	0	0	0.40	0.70	0.55	0.20	0.70	0.30	0.1984
RPA2	*36*	2	6	0	1	1	0	0	0	0.40	0.70	0.55	0.20	0.70	0.30	0.1984
SAT2	*1*	1	1	0	1	0	0	0	0	0.75	0.80	0.95	0	0	0	0.1252
RPA1	*0*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000
RPA2	*0*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000
RPA3	*0*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000
AC1	*0*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000
AC2	*0*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000
SAT1	*0*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000
SAT2	*0*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000
SAT3	*0*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000

In this example with broad categorical value functions and no capability level distinction between the two bases, many of the alternatives have identical scores. However, this is expected in an initial screening procedure when the subject matter expert is tasked to assign rough capability level characteristics to a set of platforms -- many of the platforms will fall into the same value function category. It is the task of the later detailed simulation process to break these ties based on a true physics-based performance evaluation.

Note that because the highest value function categories are not a value of 1.00, the highest possible value for an alternative to achieve is 0.8177 -- when the alternative scores in the "high" category for all nine measures. The raw score for each alternative can be translated to the percentage of possible value it achieves, shown in Table 18.

Table 18: Value achieved for all alternatives

		Option						
System	Version	Base	Route	INT1	INT2	INT3	Total Score	Percent Value
RPA1	*4*	1	2	1	0	0	0.5348	60.52%
RPA1	*5*	1	2	2	0	0	0.5348	60.52%
RPA1	*22*	2	2	1	0	0	0.5348	60.52%
RPA1	*23*	2	2	2	0	0	0.5348	60.52%
SAT1	*1*	1	1	1	0	0	0.5348	60.52%
SAT1	*2*	1	1	2	0	0	0.5348	60.52%
RPA1	*10*	1	4	1	0	0	0.4850	54.88%
RPA1	*11*	1	4	2	0	0	0.4850	54.88%
RPA1	*28*	2	4	1	0	0	0.4850	54.88%
RPA1	*29*	2	4	2	0	0	0.4850	54.88%
RPA2	*4*	1	2	1	0	0	0.4793	54.24%
RPA2	*5*	1	2	2	0	0	0.4793	54.24%
RPA2	*22*	2	2	1	0	0	0.4793	54.24%
RPA2	*23*	2	2	2	0	0	0.4793	54.24%
RPA1	*1*	1	1	1	0	0	0.4725	53.47%
RPA1	*2*	1	1	2	0	0	0.4725	53.47%
RPA1	*19*	2	1	1	0	0	0.4725	53.47%
RPA1	*20*	2	1	2	0	0	0.4725	53.47%
RPA2	*10*	1	4	1	0	0	0.4295	48.60%
RPA2	*11*	1	4	2	0	0	0.4295	48.60%
RPA2	*28*	2	4	1	0	0	0.4295	48.60%
RPA2	*29*	2	4	2	0	0	0.4295	48.60%
RPA1	*7*	1	3	1	0	0	0.4227	47.83%
RPA1	*8*	1	3	2	0	0	0.4227	47.83%
RPA1	*25*	2	3	1	0	0	0.4227	47.83%
RPA1	*26*	2	3	2	0	0	0.4227	47.83%
RPA2	*1*	1	1	1	0	0	0.4170	47.19%
RPA2	*2*	1	1	2	0	0	0.4170	47.19%
RPA2	*19*	2	1	1	0	0	0.4170	47.19%
RPA2	*20*	2	1	2	0	0	0.4170	47.19%
RPA3	*1*	1	1	1	0	0	0.4170	47.19%
RPA2	*7*	1	3	1	0	0	0.3672	41.55%
RPA2	*8*	1	3	2	0	0	0.3672	41.55%
RPA2	*25*	2	3	1	0	0	0.3672	41.55%
RPA2	*26*	2	3	2	0	0	0.3672	41.55%
RPA1	*6*	1	2	0	1	1	0.3489	39.48%
RPA1	*24*	2	2	0	1	1	0.3489	39.48%
RPA1	*3*	1	1	0	1	1	0.3270	37.00%
RPA1	*21*	2	1	0	1	1	0.3270	37.00%
RPA1	*12*	1	4	0	1	1	0.3269	36.99%
RPA1	*30*	2	4	0	1	1	0.3269	36.99%
RPA2	*6*	1	2	0	1	1	0.3145	35.59%
RPA2	*24*	2	2	0	1	1	0.3145	35.59%
RPA1	*9*	1	3	0	1	1	0.3050	34.51%
RPA1	*27*	2	3	0	1	1	0.3050	34.51%
AC2	*1*	1	1	0	1	1	0.2950	33.38%
AC2	*2*	1	1	0	2	2	0.2950	33.38%
RPA2	*3*	1	1	0	1	1	0.2926	33.11%
RPA2	*21*	2	1	0	1	1	0.2926	33.11%
RPA2	*12*	1	4	0	1	1	0.2925	33.10%
RPA2	*30*	2	4	0	1	1	0.2925	33.10%
AC1	*1*	1	1	0	1	1	0.2881	32.60%
AC1	*2*	1	1	0	2	2	0.2881	32.60%
AC2	*3*	1	2	0	1	1	0.2850	32.25%
AC2	*4*	1	2	0	2	2	0.2850	32.25%
RPA1	*13*	1	5	1	0	0	0.2839	32.13%
RPA1	*14*	1	5	2	0	0	0.2839	32.13%
RPA1	*16*	1	6	1	0	0	0.2839	32.13%
RPA1	*17*	1	6	2	0	0	0.2839	32.13%
RPA1	*31*	2	5	1	0	0	0.2839	32.13%
RPA1	*32*	2	5	2	0	0	0.2839	32.13%
RPA1	*34*	2	6	1	0	0	0.2839	32.13%
RPA1	*35*	2	6	2	0	0	0.2839	32.13%
AC1	*3*	1	2	0	1	1	0.2781	31.47%
AC1	*4*	1	2	0	2	2	0.2781	31.47%
RPA2	*9*	1	3	0	1	1	0.2706	30.62%
RPA2	*27*	2	3	0	1	1	0.2706	30.62%
RPA1	*15*	1	5	0	1	1	0.2328	26.34%
RPA1	*18*	1	6	0	1	1	0.2328	26.34%
RPA1	*33*	2	5	0	1	1	0.2328	26.34%
RPA1	*36*	2	6	0	1	1	0.2328	26.34%
RPA2	*13*	1	5	1	0	0	0.2284	25.85%
RPA2	*14*	1	5	2	0	0	0.2284	25.85%
RPA2	*16*	1	6	1	0	0	0.2284	25.85%
RPA2	*17*	1	6	2	0	0	0.2284	25.85%
RPA2	*31*	2	5	1	0	0	0.2284	25.85%
RPA2	*32*	2	5	2	0	0	0.2284	25.85%
RPA2	*34*	2	6	1	0	0	0.2284	25.85%
RPA2	*35*	2	6	2	0	0	0.2284	25.85%
SAT3	*1*	1	1	0	0	1	0.2237	25.31%
RPA2	*15*	1	5	0	1	1	0.1984	22.45%
RPA2	*18*	1	6	0	1	1	0.1984	22.45%
RPA2	*33*	2	5	0	1	1	0.1984	22.45%
RPA2	*36*	2	6	0	1	1	0.1984	22.45%
SAT2	*1*	1	1	0	1	0	0.1252	14.17%
RPA1	*0*	0	0	0	0	0	0.0000	0.00%
RPA2	*0*	0	0	0	0	0	0.0000	0.00%
RPA3	*0*	0	0	0	0	0	0.0000	0.00%
AC1	*0*	0	0	0	0	0	0.0000	0.00%
AC2	*0*	0	0	0	0	0	0.0000	0.00%
SAT1	*0*	0	0	0	0	0	0.0000	0.00%
SAT2	*0*	0	0	0	0	0	0.0000	0.00%
SAT3	*0*	0	0	0	0	0	0.0000	0.00%

Performing well on the highly-weighted INT1 sub-objective is the key to a high percentage of value achievement. However, even the best assets achieve only 60% of the possible value, so this screening process becomes important as a variety of assets are needed to achieve high total value or value across all INTs.

Four RPA1 platforms and the two SAT1 platforms provide the highest value of the alternatives because of their strong INT1 capabilities. Several other RPA1 and RPA2 platforms also achieve significant value through strength in this sub-objective.

Of the alternatives that provide INT2 and INT3 value, RPA1 alternatives provide the highest six options, followed by RPA2 and the ACs. When examining which assets provide value to different INTs, it is important to remember that only one copy of each asset is available in this simulation. Thus, RPA1 could not be selected to service both INT1 and INT2 & INT3.

AC1 and AC2 are mediocre, achieving less than 34% of the possible value, and less desirable than some RPA1 and RPA2 options for servicing INT2 & INT3. SAT3, the only option that serves solely INT3, provides low total value at 25%. SAT2, the only option that serves solely INT2, provides even lower total value at 14%. While the SAT2 and SAT3 assets are strong for their respective sub-objectives, INT2 and INT3 are simply weighted too low for these assets to provide significant overall value. It is important to remember that the numbers and values assigned here are for illustrative purposes only, as true values are known but classified. Thus, these results (i.e., lack of SAT strength) may be unintuitive and not match reality.

These results help determine not only which assets are vital, but which platforms of each asset are preferred. SAT1, RPA1, and RPA2 are the leading assets. RPA1 flying route 2 with an INT1 package provides 60.52% of the total possible value; SAT1 also achieves this value. The highest valued RPA2 platform follows route 2 with an INT1 package. Table 19 shows the best platform for each asset, with ties included.

Table 19: Best platforms for each asset

		Option					
System	Version	Base	Route	INT1	INT2	INT3	Percent Value
RPA1	*4*	1	2	1	0	0	60.52%
	5	1	2	2	0	0	60.52%
	22	2	2	1	0	0	60.52%
	23	2	2	2	0	0	60.52%
SAT1	*1*	1	1	1	0	0	60.52%
	2	1	1	2	0	0	60.52%
RPA2	*4*	1	2	1	0	0	54.24%
	5	1	2	2	0	0	54.24%
	22	2	2	1	0	0	54.24%
	23	2	2	2	0	0	54.24%
RPA3	*1*	1	1	1	0	0	47.19%
AC2	*1*	1	1	0	1	1	33.38%
	2	1	1	0	2	2	33.38%
AC1	*1*	1	1	0	1	1	32.60%
	2	1	1	0	2	2	32.60%
SAT3	*1*	1	1	0	0	1	25.31%
SAT2	*1*	1	1	0	1	0	14.17%

When beginning to create a portfolio of ISR assets, it would be advantageous to start with alternatives from this set.

The methodology developed allows for two main screening processes. First, the assets under consideration can be explored for simple value dominance. If every platform of Asset A provides less value than every platform of Asset B, Asset A can be eliminated under a rough of screening procedure. This screening applies when the goal is achieving overall value and when constraints prevent the selection of both assets. For example, if within a larger problem only one SAT asset can be selected, both SAT1 platforms (60.52%) dominate SAT3 (25%) and SAT2 (14%), so SAT2 and SAT3 can be removed from the pool of possible alternative. It must be noted that SAT2 and SAT3 provide different INT capabilities than SAT1, and removing them from the alternative pool could be detrimental to an ideal solution.

However, if a constraint states firmly that only one SAT asset can be used, SAT1 will provide the most value to the overall hierarchy. Removing just two assets (and only two

alternatives, as each asset has only one platform) still results in a large reduction in the number of portfolios for evaluation and thus the time required for evaluation.

Table 20: Alternative and combination reduction

	Original	After Screening	% Reduction
Total Alternatives	93	91	2.15%
Total Combinations	821400	205350	75.00%

As shown in Table 20, a two percent reduction in alternatives results in a 75% reduction in combinations.

This simple value dominance can dangerously eliminate versatile alternatives. Narrowing dominance to the sub-objective level, when value in a certain sub-objective is desired in addition to overall value, can help mitigate this danger. A portfolio goal may be to achieve value in a set of INT sub-objectives in addition to maximizing overall value. The capability level assessment process allows for an alternative's total value achieved to be broken down into value achieved in each sub-objective.

If every alternative for Asset A provides more value than every alternative for Asset B for a specific set of sub-objectives of interest, then Asset B is thoroughly dominated. Depending on the constraints of the problem, Asset B can be eliminated as it will not be chosen to provide value in the set of sub-objectives over Asset A.

A single sub-objective example involves SAT1, RPA2 versions that provide INT1 capability, and RPA3. Each of these assets provides INT1 capability. The value generated from the capability level of SAT1 dominates the value generated from all versions of RPA2 and RPA3 in this sub-objective category. If only one alternative can be chosen to provide INT1 capability,

SAT1 would be chosen and the INT1 versions of RPA2 and RPA3 would be screened, eliminating a large number of alternatives.

A multiple sub-objective example involves the platforms of RPA1, RPA2, AC1, and AC2 that provide INT2 and INT3 capabilities. While RPA1 and RPA2 platforms score highest in these sub-objectives, several RPA1 and RPA2 platforms also rank below AC1 and AC2. Thus, in this situation, none of the assets could be screened on total dominance. However, if there existed a third "AC3" asset that provided a value score of < 22.45% in INT2 and INT3 for all AC3 platforms, it would be dominated by the existing assets in those sub-objectives and could be eliminated.

The method just described involves screening an asset based on total dominance by another asset -- when all platforms of one asset dominate all platforms of another asset in a set of sub-objectives. In reality, this situation may be rare. The second screening method is based on alternative dominance within a specific asset. RPA1 has 37 possible platforms as a result of the combinations of its basing options, routes, and INT packages, but only one can be selected for deployment. Instead of including all 37 alternatives in the portfolio modeling process, it may be valuable to examine only a select few top scoring RPA1 platforms. The top scoring alternatives within an asset are selected for further analysis, while the remainder are screened out. For an asset such as RPA1 that has two sub-objective capability coverage options (INT1 or INT2 & INT3), it is important to screen widely enough to include RPA1 platforms that cover both areas. This way, constraints dealing with sub-objective coverage or limitations in number of assets can be met without overly-limiting the possible solutions. Thus, one would select RPA1 versions *4, 5*, *22*, and *23*, which score highest (60.52%) and provide INT1 capability, as well as RPA1 versions *6* and *24*, which score highest (39.48%) for the INT2 & INT3 package. When ties

occur, all alternatives are included. The performance is not truly identical, but appears this way due to the categorical value functions. More detailed modeling will resolve these ties and determine the true best alternative. Following this model, the alternative set is reduced to the 21 alternatives in Table 21.

Table 21: Alternative reduction based on value in sub-objective areas

		Option					
System	Version	Base	Route	INT1	INT2	INT3	Percent Value
RPA1	*4*	1	2	1	0	0	60.52%
	5	1	2	2	0	0	60.52%
	22	2	2	1	0	0	60.52%
	23	2	2	2	0	0	60.52%
	6	1	2	0	1	1	39.48%
	24	2	2	0	1	1	39.48%
RPA2	*4*	1	2	1	0	0	54.24%
	5	1	2	2	0	0	54.24%
	22	2	2	1	0	0	54.24%
	23	2	2	2	0	0	54.24%
	6	1	2	0	1	1	35.59%
	24	2	2	0	1	1	35.59%
RPA3	*1*	1	1	1	0	0	47.19%
AC1	*1*	1	1	0	1	1	32.60%
	2	1	1	0	2	2	32.60%
AC2	*1*	1	1	0	1	1	33.38%
	2	1	1	0	2	2	33.38%
SAT1	*1*	1	1	1	0	0	60.52%
	2	1	1	2	0	0	60.52%
SAT2	*1*	1	1	0	1	0	14.17%
SAT3	*1*	1	1	0	0	1	25.31%

This reduction keeps the highest-scoring alternatives and still allows for a robust portfolio selection in the face of enforced limitations. Many possibilities exist to provide high overall value and achieve value in the three INT sub-objectives, no matter asset type or total number of assets constraints.

Table 22: Alternative and combination reduction

	Original	After Screening	% Reduction
Total Alternatives	93	29	68.82%
Total Combinations	821400	10584	98.71%
Time to solve (days)	4278.1	55.1	98.71%

As shown in Table 22, this procedure reduces the total alternatives by 68.82% and reduces the number of possible portfolios by 98.71%. Originally, the time to evaluate all portfolios was 4,278 days, or 11.72 years -- an impossible amount of time. Now, the time to evaluate all possible portfolios is reduced to 55.1 days. Not ideal, but a possible evaluation time. This was a conservative screening, as many alternatives with inferior total value remained. More aggressive screening would further reduce the time for evaluation.

This process establishes a set of alternatives to serve as a starting point for a response surface search algorithm that utilizes a physics-based simulation program for true portfolio performance evaluation. Even if no alternatives are truly eliminated from the search, by providing the algorithm with a good starting point based on the set of alternatives found above, the total search time is likely reduced. Actually eliminating inferior alternatives speeds the search even more.

Sufficiency Screening.

After screening inferior assets or alternatives to reduce the number of portfolios to a more reasonable size, a complex simulation program is implemented to accurately assess portfolio performances. An algorithm searches for the highest-performing portfolio, effectively ranking portfolios as it progresses.

While determining the highest-performing portfolio is valuable, this may not be the actual goal. Often, it is more valuable to determine which portfolios are sufficient to meet the

needs of the problem, and which are not. This becomes important when cost is considered in the implementation of a portfolio.

In the ISR example, the best performing portfolio will simply use all available assets in their ideal configurations -- a trivial solution. This best portfolio may also be the most expensive, yet provide only marginal additional value over another portfolio that still sufficiently solves the problem but costs less. It is important to identify which ISR asset portfolios will meet the needs; any portfolio performing above the requirement can still be selected, though extra resources potentially required may be allocated better elsewhere.

A process is needed to define this sufficiency level, so the portfolio set can be divided into acceptable and unacceptable sets. From there, post-analysis can be performed on the acceptable portfolios based on cost and other factors. Fundamentally, portfolio sufficiency is derived from the opinions of the decision maker. As previously discussed, for many problems a rough minimum acceptable performance level of a solution is known. The difficulty is determining which portfolios achieve that performance given the inherent uncertainties in both assigning the level and determining true portfolio performance.

The sufficiency determination process for the ISR problem begins at the analyst level. The raw data collected from ISR assets is transformed into actionable intelligence by a set of analysts. An analyst who works with this data on a regular basis first creates a value function to map the characteristics of the data he receives to the value of useable information generated. Depending on the analyst's specialty area, this characteristic could be quantity of data, quality of the data, timeliness of the data, or some combination. The analyst uses past experiences and future expectations to estimate the value of information that can be created from a certain raw data input. For example, an imagery analyst may feel confident that he can provide a high level

of intelligence (i.e., 90% of the maximum value he could possibly provide) with 10 photographs a day. At three photographs a day, the value he can provide drops to 40%. Thus, a value function is created. Depending on the resolution desired, "analyst" could mean an actual individual person, or a larger analysis shop that focuses in a specific area.

After value functions are created by each analyst, the top-level decision maker is asked to estimate the value he wishes a successful portfolio to provide on a zero-to-one scale, with one being the absolute highest value imaginable. This definition depends on the specific problem under consideration. If the decision maker is determining an appropriate portfolio for the reallocation of a portion of current assets to a new mission area, he would provide a number that represents the percentage of overall value the new mission is worth, or the percentage of total information gathering capability he wishes to allocate to the new mission.

In a complete force structuring problem, such as the ISR problem under consideration, the goal is to develop a portfolio of assets that that efficiently and sufficiently allocates data to all analysts. In this way, no analyst would be flooded by and none would be starved for raw data, and all would have the resources available to perform their job. The decision maker would understand the inefficient status quo as well as the value function process that analysts performed. The decision maker then provides a number that represents the minimum level of value he deems necessary from an acceptable portfolio. Clearly, the closer this number is to one, the higher the performance needed for a sufficient portfolio. If the value of the current operational portfolio is known, the decision maker may wish for a percentage improvement on current capabilities.

Once the decision maker has provided a desired value, this number is transferred back down to the analyst level. This value is found on the *y*-axis of each analyst's value function

graph, and the value function itself maps this value level to a certain level of data characteristic on the *x*-axis, as shown in Figure 17.

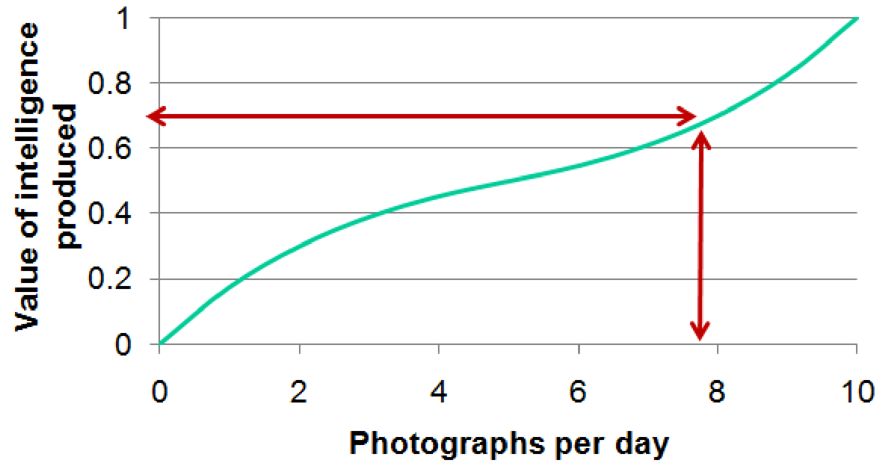


Figure 17: Analyst value function

Now, the decision maker's single input has been pushed throughout to determine the minimum data each analyst should receive. While the analysts have completely different *raw data* requirements, each will be provided whatever amount necessary to achieve the same *value* that results from processing that data. This avoids the disparity in data provision that prevents optimal collective intelligence generation.

The sufficiency level is set at the ability to provide this level of data. A portfolio can be evaluated on whether its performance results in sufficient data to meet the need of each analyst. If a portfolio can meet this criterion, it is deemed sufficient and set aside for further post-analysis. If a portfolio cannot meet this data criterion, it is deemed insufficient and screened from further study. This screening procedure based on data sufficiency is thus used to further reduce the number of portfolios that undergo final analysis to only those that sufficiently solve

the problem. In the post-analysis phase, factors such as cost determine the selection of an ideal portfolio.

IV.D Summary

The purpose of this chapter was to provide an application of several novel screening techniques to an actual USSTRATCOM JFCC-ISR hierarchy with a sample alternative data set. The methodology developed here transforms a broad performance-based hierarchy designed for portfolio evaluation to a simple capability-based hierarchy designed for alternative evaluation. Eliminating a number of alternatives results in significantly fewer portfolios, allowing sufficient portfolios to be evaluated against the performance-based hierarchy and examined on a reasonable timescale.

Conclusions and Recommendations

V.A. Introduction

The continuous advancement of technology has provided incredible opportunities for the Department of Defense to achieve its mission. Innovation in hardware and software has allowed for an explosion in the number of intelligence, surveillance, and reconnaissance platforms available. This progress has coincided with the wars in Iraq and Afghanistan, allowing United States efforts to be aided by more, better data.

A by-product of new ISR technology becoming available immediately when needed has been the inefficient deployment of such assets. Without proper asset distribution based on platform performance and user needs, capability is wasted. Some analysis units are flooded with data impossible to process in a timely manner, while others starve for data that could provide actionable intelligence.

The establishment by USSTRATCOM JFCC-ISR of an intelligence objectives hierarchy is a good start to improving asset deployment. Next, it must be determined what minimum level of data is necessary in which analysis areas so that an appropriate portfolio of ISR assets can be generated to sufficiently meet the objectives. Difficulty arises as there are hundreds of ISR platform variations leading to an astronomical number of possible portfolios. This research developed methodologies to confront both of these challenges. A process was explored to eliminate poor ISR alternatives and thus reduce the number of portfolios, followed by a procedure to define portfolio sufficiency.

V.B. Research Contributions

The purpose of this research was to contribute to the field of Decision Analysis a new methodology to examine multiobjective decision problems with combinatorial alternative sets. Specifically, the procedures developed apply when each objective is evaluated through the same set of sub-objectives, a common decision problem characteristic. This research established processes to reduce the size of the alternative set through intelligent screening and to determine the sufficiency of portfolios of alternatives.

The first contribution was in the area of alternative screening. Many problems feature a large number of alternatives, especially as each variation of a general solution can be considered a new alternative. When the decision maker may select a portfolio of these alternatives to generate a solution, the number of possibilities becomes enormous; evaluating all portfolios is difficult.

Eliminating a small number of alternatives can drastically reduce the number of possible portfolios. A procedure was developed to reduce the multi-objective performance-based hierarchy to a simple capability-based hierarchy. This allowed for assessment of alternative contribution to the overall goal through both basic capability and slightly more advanced estimated performance. With these assessments made, low-performing alternatives may be eliminated depending on the constraints of the specific problem under evaluation. This procedure commonly reduces the number of possible portfolios by greater than 95%.

The second contribution to the field of decision analysis was in the area of alternative sufficiency. It is valuable to sort alternatives, or portfolios of alternatives, into two groups: those that successfully meet the minimum requirements of the problem and those that fail to do so. Then, the failed alternatives can be removed from further consideration.

In problems where the decision maker is distant from the lowest tier in the evaluative hierarchy, the performance valued by the decision maker is difficult to translate into the bottom tier measure requirements an alternative must provide. Thus, a method was developed to push the decision maker's needs down the hierarchy. This process combined performance or confidence requirements from the decision maker with the knowledge of those familiar with the specifics of the bottom tier of the hierarchy, thereby determining the level of measure performance necessary to sufficiently achieve the goal. A portfolio of alternatives could then be rated on whether it provided an acceptable level of performance in each measure and thus sub-objective.

V.C. Recommendations for Further Research

This research developed a methodology that was shown to successfully achieve its mission of eliminating alternatives. A theoretical set of alternatives was analyzed and screened according to various constraints, demonstrating the ability of the procedure to generate a large percentage reduction of the portfolio space.

Future research should attempt to validate this methodology through application to a full problem where the performance of a large number of portfolios is known. The procedure can be followed to eliminate alternatives; according to the theory presented in this research, the best-performing portfolios should be comprised of alternatives that remain after screening.

These validation studies are necessary to determine the rigor of the methodology and identify potential process improvements. Additional research can focus on refining the methodology and expanding the universe of problems to which it can be applied, or adapting it for a new type of problem. Finally, an expansion of the portfolio sufficiency process described

here can be performed. Areas of investigation could include sensitivity analysis, sub-objective performance to objective achievement mapping, and minimum sub-objective achievement issues.

V.D. Conclusions

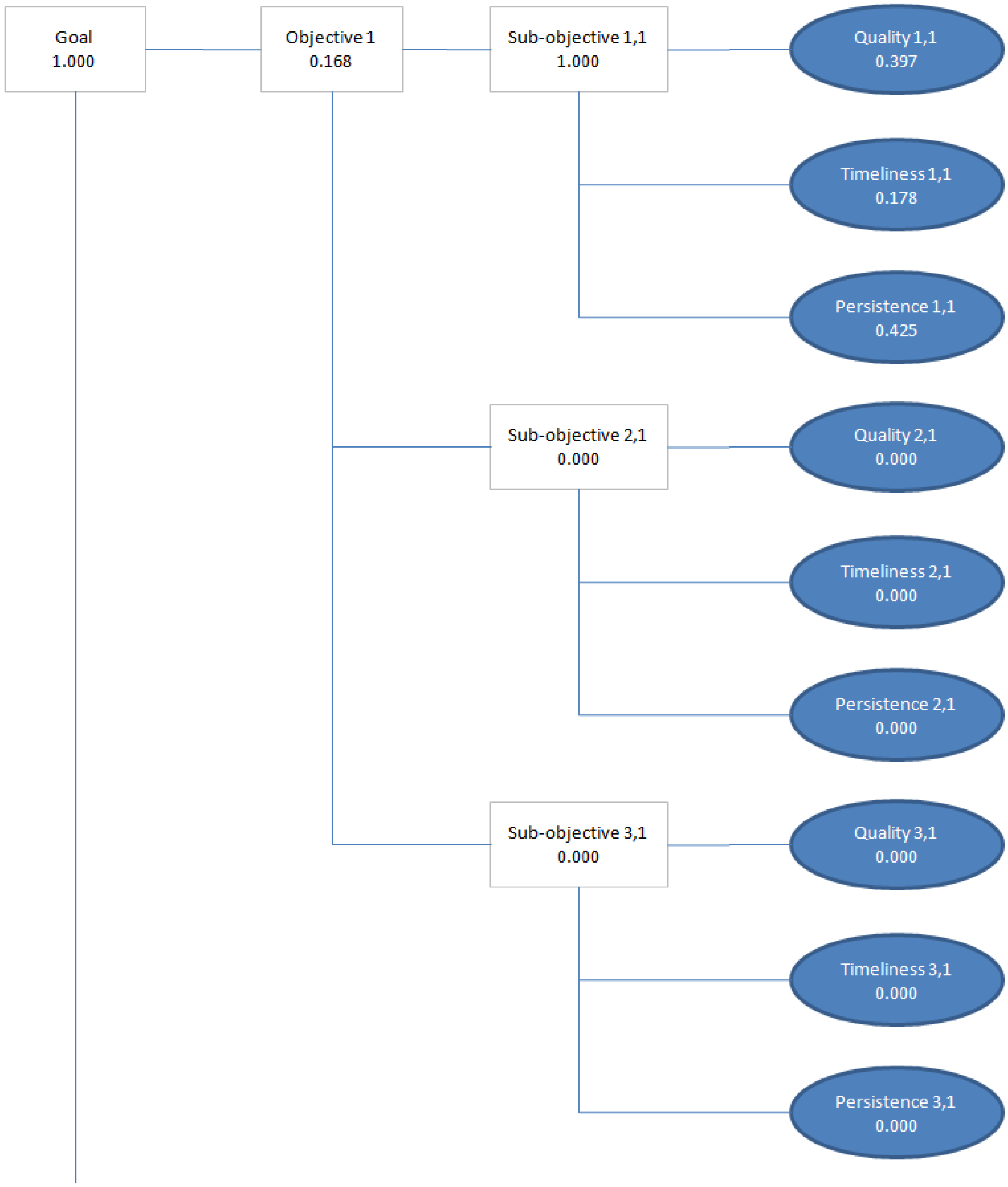
In a world growing more interconnected and data driven, decision makers face problems more complex than ever before. Failing to give a problem the careful study it deserves can lead to a poor decision with potentially disastrous results. At the very least, the decision maker may fail to obtain all the value possible.

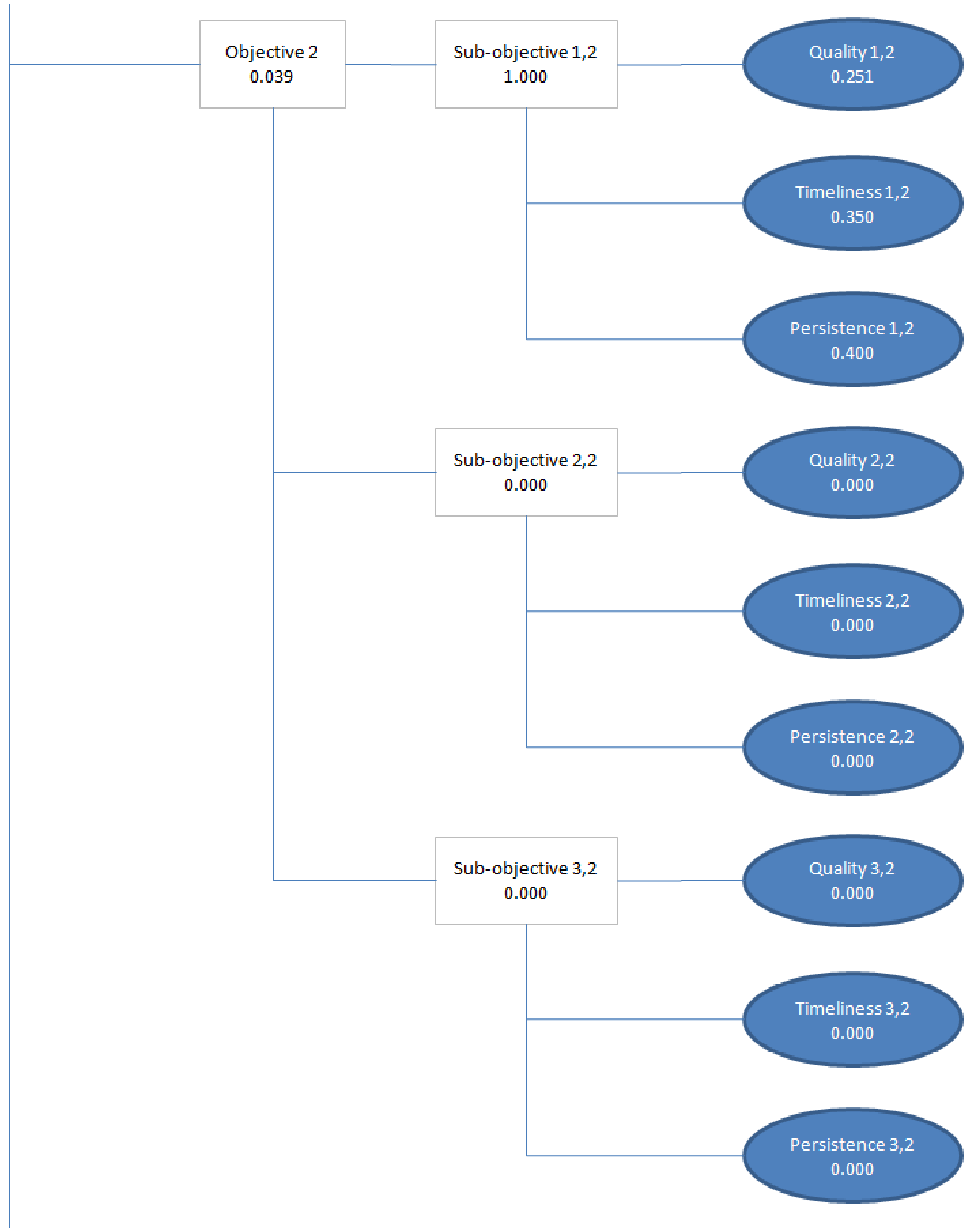
By reducing the complexity of the hierarchy, the analyst can reduce the size of the alternative set and number of potential portfolios. Eliminating poor alternatives allows for better concentration on the remaining solutions, improving the chances that a good decision will be made.

The new methodology developed in this research for screening alternatives and determining sufficiency criteria was applied to the USSTRATCOM hierarchy with a sample alternative set. The results demonstrated that a capability-based assessment can greatly reduce the number of alternatives, making performance evaluation of the portfolios comprised of good alternatives more feasible. Applying this process to the full ISR force sizing problem will allow for an ideal mix of assets to be identified. This portfolio will provide the data needed to generate quality intelligence to the benefit of the military and the United States.

Appendix A.

JFCC-ISR Hierarchy




Objective 2
0.039
Sub-objective 1,2
1.000
Quality 1,2
0.251
Timeliness 1,2
0.350
Persistence 1,2
0.400
Sub-objective 2,2
0.000
Quality 2,2
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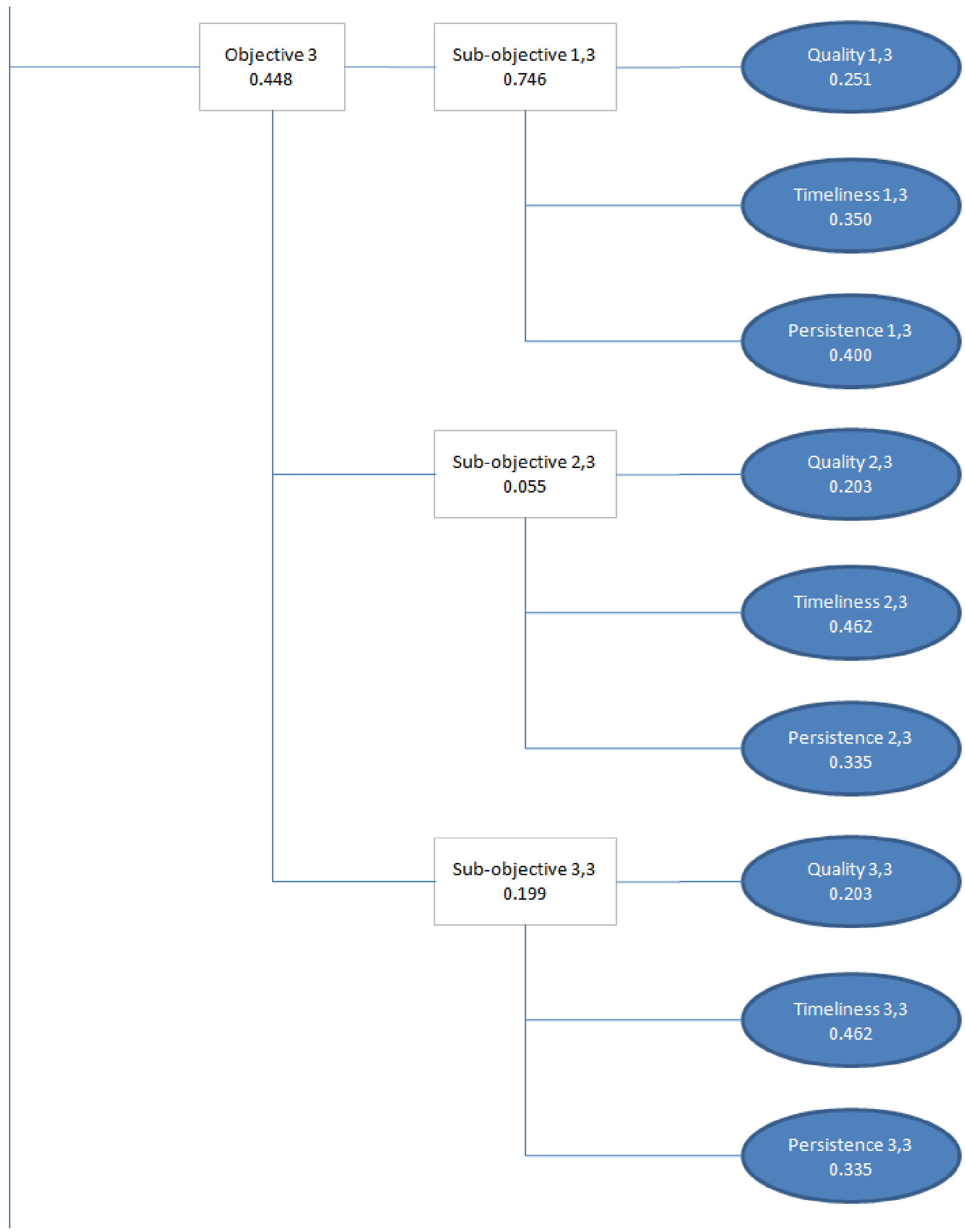
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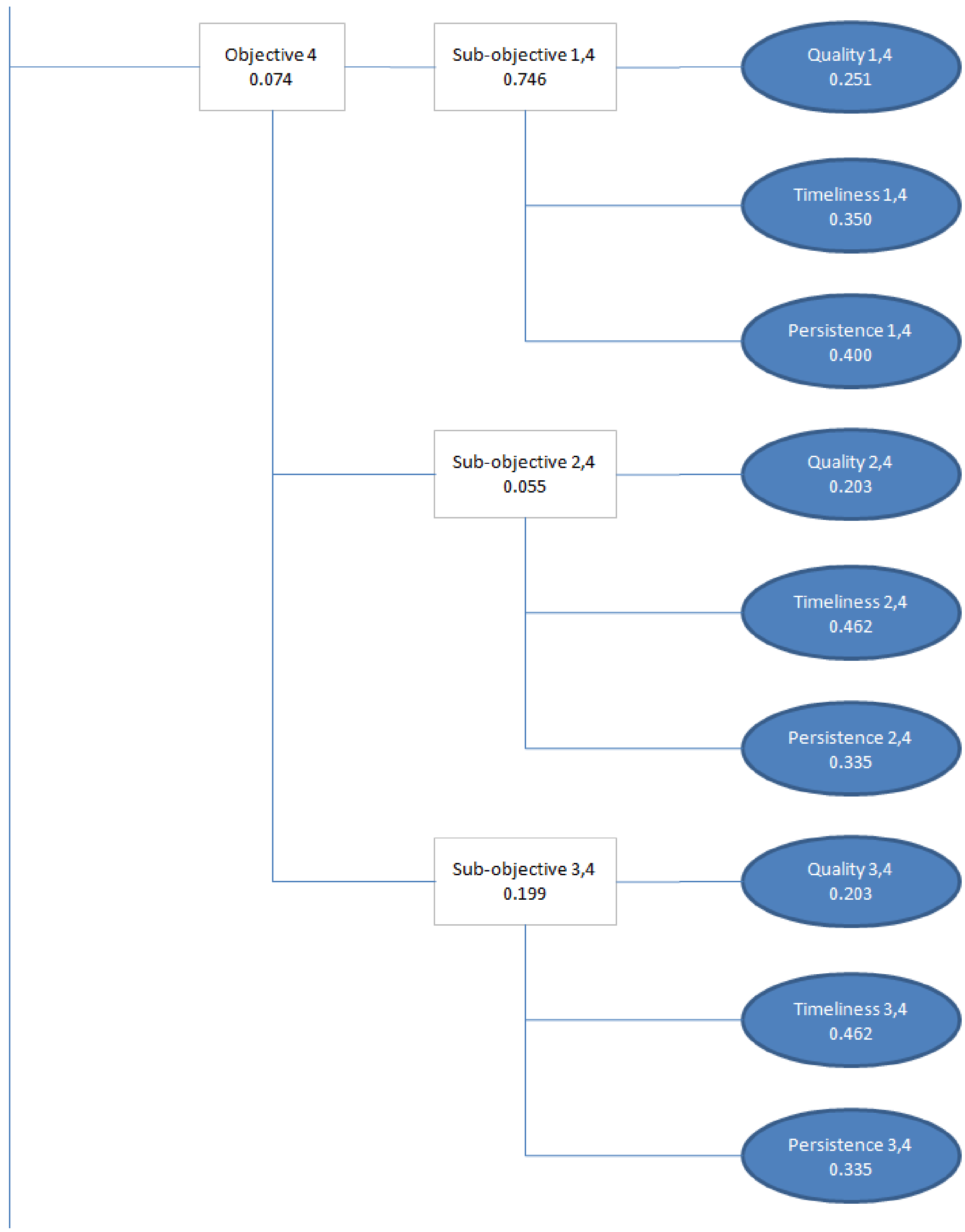
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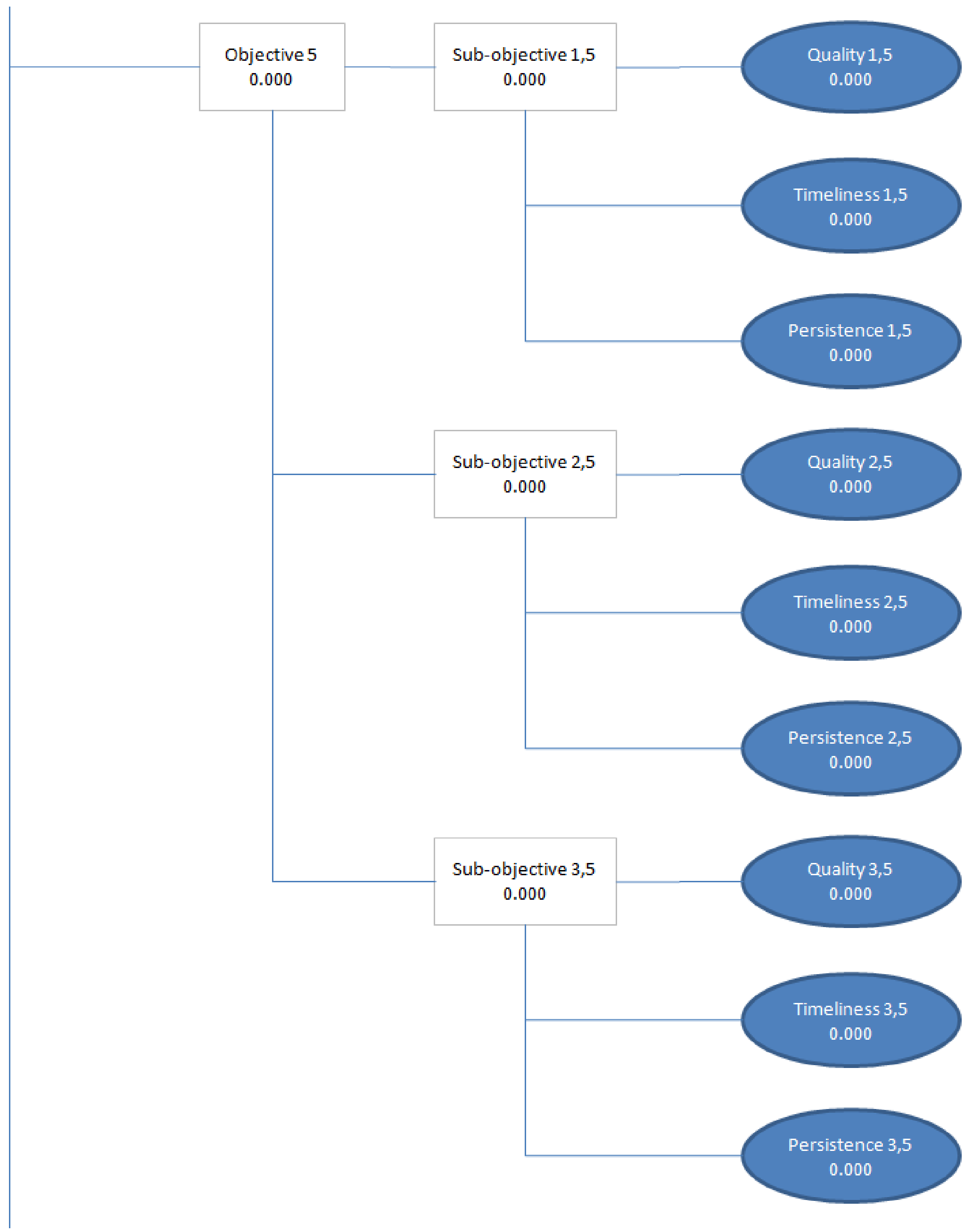

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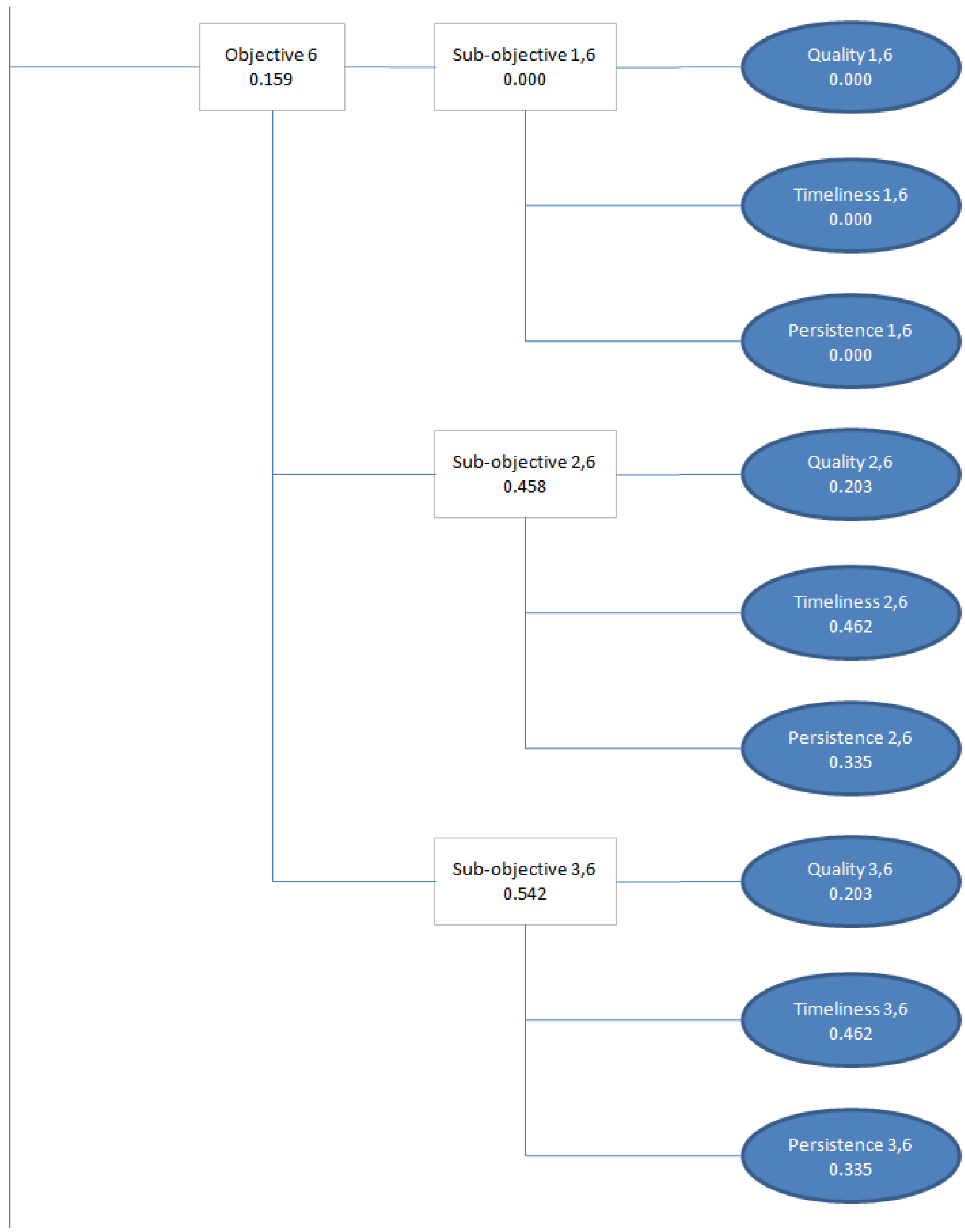
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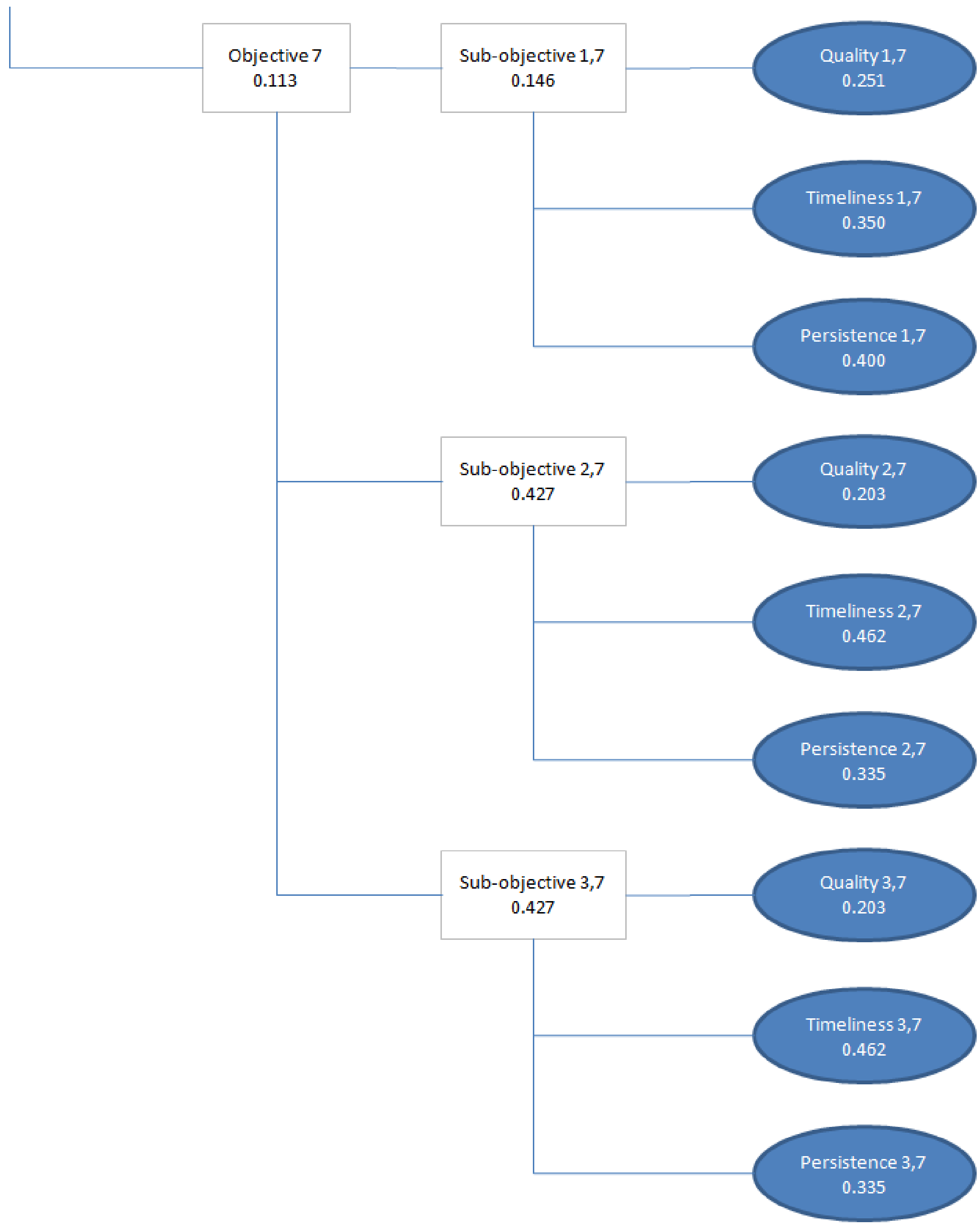
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Appendix B.

Blue Dart

Researchers at the Air Force Institute of Technology (AFIT) are leading the way on ground breaking research to help commanders obtain the intelligence, surveillance, and reconnaissance (ISR) assets needed to fight and win wars. The recent United States military efforts in Iraq and Afghanistan have spurred the development of innovative surveillance and reconnaissance technology to meet increasing data requirements and generate actionable intelligence. In today's complex ISR world, there are billions of combinations of platforms, sensors, and concepts of operations possible to help a commander understand the ever-changing battlefield. The time to model and evaluate the effectiveness of these combinations, even with the latest advancements in computing technology, is prohibitive, on the order of many years. This is unacceptable given today's immediate and crucial operations.

AFIT researchers are engaged in advanced study of ideal ISR asset distribution to optimize intelligence gathering. New assets have been rapidly, but inefficiently, deployed; poor coordination across the Department of Defense has led to a failure to meet the needs of the many units that require appropriate information on a timely basis. Some organizations drown in data as numerous assets stream terabytes of data to be processed. Meanwhile, other groups suffer from a lack of the data needed to develop actionable intelligence. AFIT is developing sophisticated mathematical models to ensure an ideal portfolio of ISR assets is deployed to successfully meet the complexity of today's joint environment.

Difficulty arises when attempting to identify the ideal portfolio. The Department of Defense possesses many different types of assets to provide ISR capability. For each asset, multiple equipment packages may be installed to generate different types of data. Assets can be

used in a number of locations in a variety of ways. These variables and others lead to many possible usage alternatives for a single asset. In the context of Department of Defense total assets and theatre deployment options, an enormous number of possible portfolios are generated through the combination of different asset alternatives. Computer modeling of every portfolio's performance requires an impossibly long time on even the fastest of computer systems. A process is needed to select more efficiently an ideal portfolio.

AFIT has invented a two-part methodology for a class of portfolio selection problems such as the ISR situation previously described, when there exist multiple objectives that are all judged on the same hierarchical metric set. First, a novel capability-based screening process was developed to evaluate ISR asset alternatives on intended capability through the reduction of the multiobjective performance hierarchy. Poor alternatives are eliminated, reducing the size of the alternative set. Removing only a few alternatives greatly reduces the number of possible portfolios, allowing for better examination of the remaining portfolios.

Next, a method was developed to define portfolio sufficiency according to the requirements of the decision maker. The portfolios remaining after the capability-based screening are then evaluated on a performance basis to determine sufficiency or not. With a set of sufficient portfolios comprised of well-performing alternatives, higher resolution post-analysis methods can be applied to choose a solution.

This two-part procedure was applied to an ISR objective hierarchy developed by the United States Strategic Command Joint Functional Component Command for Intelligence, Surveillance and Reconnaissance. After deconstructing the hierarchy, a set of representative alternatives were evaluated and a variety of screening procedures were applied to demonstrate the significant reduction in the number of portfolios possible. In one such screening process,

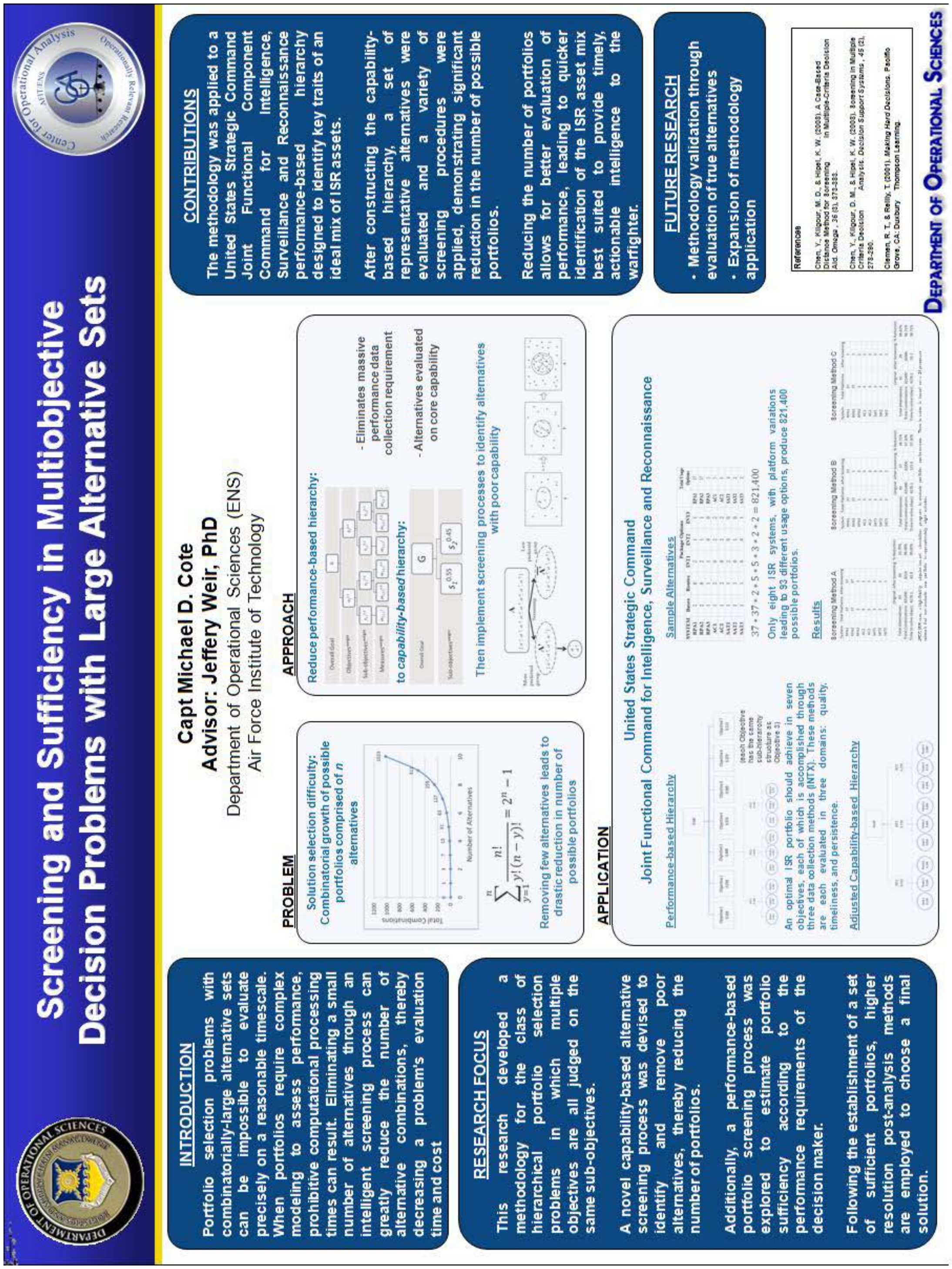
researchers were able to reduce the amount of time needed to examine good force mixes from 11 years to two months. This process allows for more resources to be dedicated to estimating the true performance of the sufficient portfolios; new systems can still be fielded rapidly, but now optimized to help the soldiers, sailors, airmen and marines in the field.

The procedure developed at AFIT and applied to ISR distribution can be generalized to any complex multiobjective problem with the hierarchical structure described in which a portfolio of alternatives is permitted. Many military force structuring problems use this type of hierarchical decision making structure. Eliminating poor alternatives initially through an intelligent screening process, as well as only focusing on sufficient portfolios, can greatly reduce the number of portfolios under consideration. This smaller universe of solutions increases the likelihood the ideal or a near-ideal solution will be selected. In an environment with limited resources, the work of AFIT's researchers to optimize assets may prove the difference between failure and success.

The views expressed in this article are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the US Government.

Appendix C.

Poster



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Vita

Capt Michael Cote graduated from South Burlington High School in South Burlington, Vermont, in 2002. He then enrolled in the Pratt School of Engineering at Duke University, concentrating in biomedical engineering. Additionally, Michael enlisted in the Air Force Reserve Officer Training Program. In May 2006, he graduated with a bachelor of science degree and commissioned as a 2nd Lieutenant in the United States Air Force.

Michael was then assigned to the Air Force Research Laboratory at Wright-Patterson Air Force Base, Ohio, to serve as a developmental research engineer. His responsibilities included developing research protocols, managing test programs and contracts, and writing technical reports on innovative military technology. While assigned to the laboratory, Michael enrolled part-time in the operations research program at the Air Force Institute of Technology, also located at Wright-Patterson AFB. After several years of coursework and research, he will graduate with a master of science in operations research.

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Portfolio selection problems with combinatorially-large alternative sets can be impossible to evaluate precisely on a reasonable timescale. When portfolios require complex modeling for performance assessment, prohibitive computational processing times can result. Eliminating a small number of alternatives through an intelligent screening process can greatly reduce the number of alternative combinations, thereby decreasing a problem's evaluation time and cost. A methodology was developed for the class of hierarchical portfolio selection problems in which multiple objectives are all judged on the same sub-objectives. First, a novel capability-based alternative screening process was devised to identify and remove poor alternatives, thereby reducing the number of portfolios. Then, a performance-based portfolio screening process was explored to estimate portfolio sufficiency according to the performance requirements of the decision maker. Following the establishment of a set of sufficient portfolios, the analyst can employ higher resolution post-analysis methods to choose a final solution. Finally, the methodology was applied to a portfolio selection problem in which the United States Strategic Command attempts to select an ideal mix of intelligence, surveillance, and reconnaissance assets. After deconstructing the actual objective hierarchy, a set of representative alternatives were evaluated and a variety of screening procedures were applied to demonstrate significant reduction in the number of possible portfolios.

15. SUBJECT TERMS
Multicriteria decision analysis, portfolio selection, alternative screening, sufficiency, ISR

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